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Innovative Applications of O.R.

Applying integrated DEA/AHP to evaluate the economic performance of local governments in China

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ABSTRACT

This paper aims at integrating data envelopment analysis (DEA) and analytic hierarchy process (AHP) to evaluate the economic development achieved by local governments in China. Since most similar evaluations are multi-objection problems, which both DEA and AHP are capable of solving, the integration of these two approaches is shown to be even more powerful. The proposed integrated DEA/AHP model can evaluate and rank different alternatives. In addition, a time-scale comparison of the economic performances of local governments in China was carried out using the malmquist productivity index (MPI), which indicated that there is a trend of economic growth. However, empirical results indicate that after discounting the advantages of location and political connections, the east district provinces of China do not have superior economic performance or a better MPI index, as compared with other districts. This result is contrary to our original hypothesis.

1. Introduction

The world has changed drastically over the past few decades, especially economic issues. Many developing countries like as BRICs (Brazil, Russia, India and China) are becoming influential in the economic growth of the world; among those nations, China has achieved the highest level of economic development and growth and is endeavoring to attract foreign direct investments (FDI) to successfully develop their economy. Additionally, China has the largest market and the most important base of manufactured products in the world. Its major strength is an abundance of skilled and inexpensive manpower. All facets of China's economy have exhibited growth trajectories, suggesting that it will remain attractive to investors. In 2001, China joined the World Trade Organization (WTO). After that time, China's economic development has grown at a higher rate than any other nation in the world, 10.7%. This is higher than the average worldwide GNP growth rate of 5.1% in 2006. In addition, in 2006, China had a foreign exchange reserve approaching 2000 billion USD, a national economic contribution to the world of approximately 13%, and was the third largest trade country as well as possessing the fourth largest economic entity. Additionally, the FDI growth rate was 4.5%, fourth in the world. All relevant information in the 2007 Chinese trade yearbook indicates that it has become an integral player in the world economy.

Although China has taken progressive steps in economic development, there still exist significant differences among different regions, and it is a commonly held conception that the economic development of the coastal east region is better than that of the middle and west regions. Even local governments have taken different measures for major initiatives of industrial development, simplification of investment procedures, enactment of investor-friendly laws, liberalization of trade policy, safeguards of intellectual property rights, etc. Significant variation may also be due to location, support from the central government and the management effectiveness of local governments.

DEA and AHP are methods that have been extensively used to evaluate and rank multi-objective decision alternatives. This paper aims to clarify and understand the different phenomena between regions and to the rank economic performance of local governments using an integrated quantitative (DEA) and qualitative (AHP) approach. Moreover, we hope to examine the true economic performance of every local government in China and to provide a metric by which to compare them after accounting for the advantages given by location and political connections.

2. Literature review

AHP was developed by Saaty in 1980. For over 20 years, this approach has been used and studied extensively and has been applied especially to multi-criteria decision making (MCDM).

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AHP also has been applied in several different fields, such as activity planning, alternative choosing, optimization, resource allocation, conflict resolution, etc. (Ahmad et al., 2006). Furthermore, AHP has been used to evaluate multi-objective design alternatives from Muther's systematic procedure (1973) for facility layouts and to integrate mathematical linear approaches such as Linear Programming (LP), Integer Linear Programming (ILP), Mixed Integer Linear Programming (MILP), Goal Programming (GP), and Dynamic Programming (DP) (Vaidya and Kumar, 2006); Ho (2008) found some researchers had focused on integrating this method with Fuzzy Theory, Artificial Neural Networks (ANN), cost-benefit analysis, Quality Function Deployment (QFD), SWOT analysis, and simulation approaches, among others. AHP software, called the Multi-Media Authorizing System (MAS), has been in use since 2002 (Lai et al., 2002). This software uses the group decision-making technique, which involves six software engineers. MAS has been used to evaluate numerous products. The decision tool for the selection of advanced technology is another proposed model (Kengpol and Brien, 2001). This model integrates a cost-benefit analysis model, a decision-making effectiveness model, and a common criteria model and is available from Time Compression Technologies (TCT).

The DEA initially developed as the CCR model by Charnes et al. (1978) and the BCC model by Banker et al. (1984) have been used for the purpose of evaluating the relative efficiency of similar economic production systems. Studies covering a wide array of empirical work, such as evaluating the socio-economic performance of nations during the last decade, have made it clear that the model must be flexible (Golany and Thore, 1997). Consequently, a number of alternative DEA models have been proposed. Even so, there is often a need for customization of the model to a specific application environment. To address this need, a variety of model extensions that increase the flexibility of DEA models have been proposed. The common set of weights (CSW) model can be applied to all DMUs and their efficiencies to solve a single problem. A method for ranking DMUs has been presented (Jahanshahloo et al., 2005). DEA has been used for the comparative performance analysis of governments (Ramanathan, 2006a). The advantages of applying DEA to the rank economic performance of governments has been comprehensively discussed in several studies, including works by Charnes et al. (1994) and Farrel (1957) among others. A model without inputs or outputs was deployed by Adolphson et al. (1992) as a solution to the superconducting supercollider; a model with pure input but no outputs was also developed. Lovell and Pastor (1999) developed radial DEA models without inputs or outputs based on the above model have shown that (i) a CCR model without inputs (or outputs) is meaningless; (ii) a CCR model with a single constant input (or with a single constant output) coincides with the corresponding BCC model; (iii) a BCC model with a single constant input (or a single constant output) reduces to a BCC model without inputs (or outputs); and (iv) all BCC models, including those without inputs (or outputs), can be condensed to models having one less variable (the radial efficiency score) and one less constraint (the convexity constraint).

There have been limited studies regarding both DEA and AHP methods. Integrated DEA and AHP models are popular in facility layout design. Yang and Kuo (2003) proposed a DEA and AHP approach to a facility layout design (FLD) problem. A computer-aided layout-planning tool, Spiral, has been used to generate a considerable number of layout alternatives, as well as to generate quantitative decision-making unit (DMU) outputs. A weighting of the qualitative output performance measures by DEA/AHP has been used to solve multiple-objective layout problems. However, this approach only considers a constant input case that is different from the standard DEA model, because the cost associated with a change incurred at the layout design stage is usually negligible. Therefore, a Banker–Charnes–Cooper (BCC) model without inputs has been adopted for solving the layout performance frontiers problem. In this field of study, the Charnes–Cooper–Rhodes (CCR) model has been applied to quantitative and qualitative data, transforming the fractional program to an ordinary linear program. In a similar work, Ertay et al. (2006) integrated DEA and AHP for facility layout design (FLD) in a manufacturing system, and presented a decision-making methodology based on data envelopment analysis (DEA) that used both quantitative and qualitative criteria to evaluate the FLD. Takamura and Tone (2003) presented a combined DEA-AHP approach to address the relocation of several government agencies from Tokyo and to compare alternative locations. Saen et al. (2005) proposed a combined DEA-AHP approach to measure the relative efficiency of slightly non-homogeneous decision-making units (DMUs). Since some DMUs lack one or more features (i.e., input and/or output), the AHP was used to provide a real-world estimate of missing values for the DMU. To do this, two alternatives were compared. The alternatives include (i) DMUs that lack the feature(s) and (ii) the series means of other DMUs. The data for the mean of other DMUs was obtained by taking the mean of each feature of all of the DMUs, except for the one that has the missing value. The data was assumed to be normally distributed.

In recent years, some researchers have endeavored to make variety on this domain. Azadeh et al. (2008) integrated DEA and AHP with computer simulation for railway system improvement and optimization; they considered both quantitative and qualitative variables for efficiency assessment and performance optimization by integration simulation. Korpela et al. (2007) proposed an approach for selecting the warehouse operator network by combining DEA and AHP. DEAHP (data envelopment analytic hierarchy process) is a new model that has been developed by Ramanathan (2006b); it is a hybrid methodology of DEA and AHP, used to prove that DEA correctly estimates the true weight when applied to a consistent matrix formed using a known set of weights. The use of DEA was further proposed to aggregate the local weights of alternatives in terms of different criteria to compute the final local weight. Sevkli et al. (2007) used the DEAHP model to evaluate supplier selection; this study focused on one of the most important subjects in supply chain management and provided a better decision for supplier selection using appropriate quantitative approaches.

3. Study framework

The proposed method and hierarchical framework for this study are shown in Fig. 1, which diagrams the procedure and details the research steps. The focus of this study, which integrates DEA and AHP approaches, is to compare local Chinese governments.

3.1. Analytic and evaluation methodology

The first step in this study is to identify which variables are important to the analysis and measurement of the indices of AHP and DEA, followed by weighing and comparing the efficiency of the alternatives. The China People's Daily (2008) published an article entitled "Report of local government and official performance evaluation in China", which indicated that other important factors in addition to the GDP should be used as measuring indices. These include the level at which development is maintained, harmony of the society, work ethic and morality, economic growth rate, Engel's coefficient, environmental quality, etc. In addition, Unite state officials in researches at Oregon State University have presented additional major economic indices: level of employment diversification, creation of new enterprises, professional service, R&D, personal income, international trade growth, net growth of employment, economic diversification, investment, expenses of employee, labor income, labor poverty percentage, and language ability (Thiel and

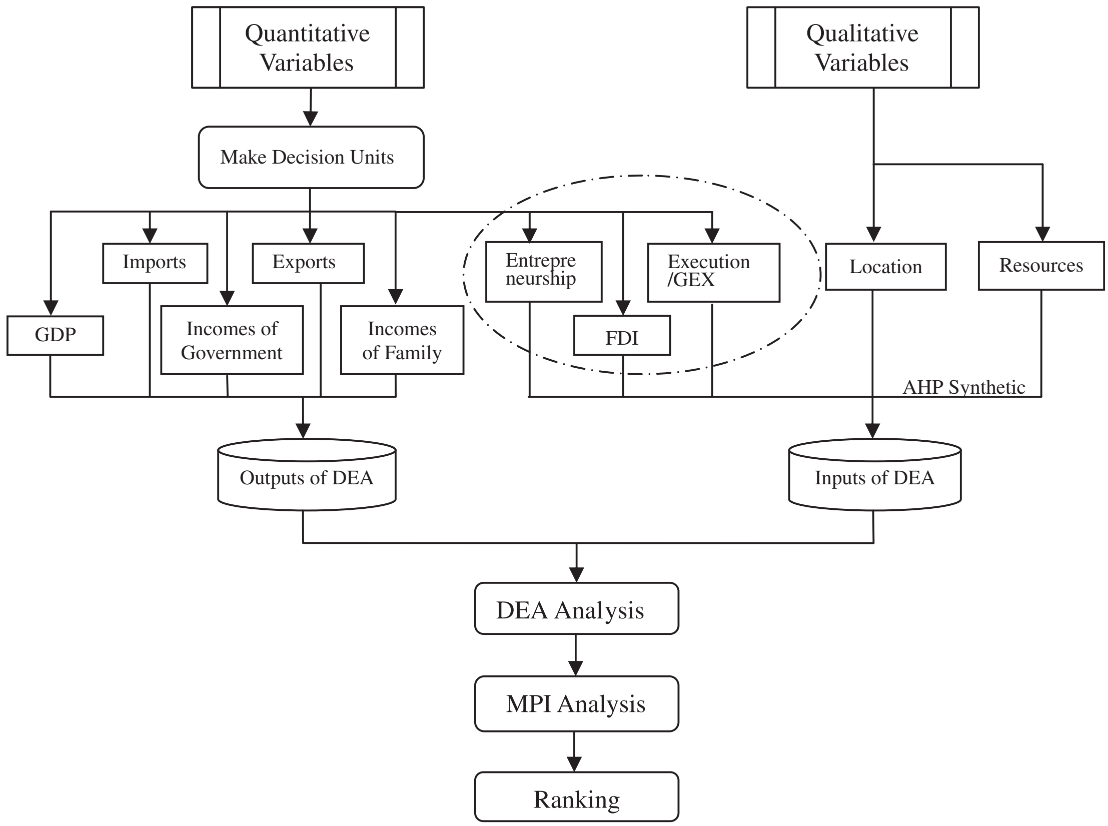


Fig. 1. Study framework.

Leeuw, 2002). Recently, Virginia state suggested five new performance measuring indices: the input index (ex; total working cost, actual labor work hours), output index (ex: rail road, officials, public affairs), outcome index (ex: death rate of traffic accidents), efficiency index, and quality index (DPB of Virginia, 1995). The Taiwanese central government also presented economic performance indices to evaluate local governments, which included an index category, a direction (positive or negative), and an attribute (CPA of Taiwan government, 2006), as shown in (Table 1).

After reviewing the above information and the relevant literature, we selected measuring indices that are independent and representative of China. Consequently, ten correlative measuring indices were used as decision variables during analysis. Since the variables have different attributes and characteristics, they were divided into two groups. Two of the ten variables are uncontrollable and are used in the AHP analysis, while the other eight are controllable and used in the DEA analysis. Each of the variables described in detail in Table 2. The geography location (GLO) and politic & economic resources (PER) variables require AHP since they are qualitative attributes, the result of synthetic weights which become input data to the DEA model; Although government execution (GEX), foreign direct investment (FDI), Entrepreneurship (EPS) etc. are controllable variables, the practical consideration are attributed to the inputs of DEA model in this study; The other variables, including Gross Domestic Product (GDP), Imports (IMP), Exports (EXP), Incomes of Government (FIN), and Incomes of Family

Table 1
Economic performance index of Taiwan local government.

Category	Index	Index direction	Index attribute
Finance	Average financial debts per person	–	Outcome
	Annual total expenditure	–	Outcome
Industry	Number of enterprises	+	Input
	SMB total payment	+	Outcome
Transportation	Highway transportation flow	+	Input
	Average commute hours	–	Outcome
Rate of unemployment	Rate of unemployment	–	Outcome
National income	Average citizen income	+	Input
Tax system	Annual total local tax	+	Input
Consumer protection	Response time per complaint	–	Process
Information technology (IT)	Percentage with a home computer	+	Outcome
	Percentage with internet access	+	Outcome
	Percentage using mobile phones	+	Outcome
Tourism	Growth rate of tourism	+	Outcome

Data sources: prepared by this study.

Table 2
Variables' attribute used in the study.

	Description	DEA attribution
(1) Uncontrollable variables/abbreviation		
Geography location/GLO	Location variable expresses mainly the convenience of economic development.	Synthetic weights of AHP analysis transformed into DEA inputs
Politic & economic resources/PER	This variable expresses how easily local governments receive political and economic resources from the central government	
(2) Controllable variables/abbreviation		
Government execution/GEX	This variable expresses the executive validity related with the economic performance of local governments	input
Foreign direct investment/FDI	Direct capital investments from foreign enterprises.	Input
Enterprises/EPS	Entrepreneurship measured by new enterprises each year	Input
Gross domestic product/GDP	Gross domestic product of each local government	Output
Imports/IMP	Total annual foreign imports	Output
Exports/EXP	Total annual domestic exports	Output
Incomes of government/FIN	Total annual financial income of local governments	Output
Incomes of family/FAM	Total family income per family within the local government region	Output

Data sources: prepared by this study.

Table 3
Decision making units (DMUs)

DMU	DMU1	DMU2	DMU3	DMU4	DMU5	DMU6	DMU7	DMU8
Name	Beijing municipality	Tianjin municipality	Liaoning province	Shanghai municipality	Jiangsu province	Zhejiang province	Fujian province	Shandong province
District	East	East	East	East	East	East	East	East
DMU	DMU9	DMU10	DMU11	DMU12	DMU13	DMU14	DMU15	DMU16
Name	Guangdong province	Hebei province	Sanxi province	Jilin province	Heilongjiang province	Anhui province	Jiangxi province	Henan province
District	East	Central	Central	Central	Central	Central	Central	Central
DMU	DMU17	DMU18	DMU19	DMU20	DMU21	DMU22	DMU23	DMU24
Name	Hubei province	Hunan province	Neimenggu	Guangxi province	Chongqing municipality	Sichuan province	Guizhou province	Yunnan province
District	Central	Central	West	West	West	West	West	West
DMU	DMU25	DMU26	DMU27	DMU28	DMU29	DMU30	DMU31	
Name	Xizang (Tibet)	Shanxi province	Gansu province	Qinghai province	Ningxia Hui regions	Xinjiang Uygur	Hainan province	
District	West	West	West	West	West	West	East	

Data sources: prepared for this study.

(FAM) etc. are attributed to outputs that can be directly analyzed with the DEA model.

The next steps involve the use of the analytic tools of the DEA frontier and the DEAP2.1-XP software package and are as follows: Expert Choice was used for AHP analyzing to get synthetic weights, the qualitative variable data were analyzed with Expert Choice to obtain available local weights, which were transformed to input variables for the DEA model. The DEA analysis was performed via Radial DEA models without inputs (Lovell and Pastor, 1999) and with the complete model of Charnes et al. (1978); the differences of both models were then compared. Consequently, efficiency scores were generated, and these scores were used to discriminate which DMUs (Decision Making Units) are better. The rankings for all of the DMUs used to evaluate economic performance and the meaning of the DMUs will be explained in the next section.

Finally, time series analysis was used to measure local governments' economic growth trends. Window analysis (WA) and malmquist productivity index (MPI) are two valuable analysis models and have been applied and extended to MPI, the window malmquist index (WMI), and the output-oriented Malmquist Index models. This study uses the output-oriented MPI model.

3.2. Decision making units (DMUs) generation

In 2008, there were 23 provinces, 4 municipalities, and 4 autonomous regions in China. The 31 total local governments were situated within the zones of three different districts (see Table 3), and for the 31 Decision Making Units (DMUs) used in this study, we analyzed the economic performance with both DEA and AHP methods.

It is a common belief that the local governments of the east districts are wealthier and have more abundant resources than the middle and west districts. This study aims to determine the veracity of this assumption. Therefore, we not only focus on the evaluation of different districts, but of all local governments. We believe that local governments have a greater impact on DMUs than larger districts. However, since 31 local governments are present, it is not easy to differentiate between the economic performances of each.

3.3. AHP for qualitative performance evaluation

AHP is a multi-criteria decision making method that uses hierarchical or network structures to represent a decision problem and then develops priorities for the alternatives based on the decision-maker judgments throughout the system (Saaty, 1980). AHP is also a kind of value function method; the reason for adopting AHP, especially for qualitative performance data, is the fact that qualitative factors are often complicated and may conflict with each other. Additionally, user acceptability and confidence in the analysis provided by the AHP methodology is high in comparison with that of other multi-attribute decision approaches (Zakarian and Kusiak, 1999). Other benefits of AHP include: a systematic way for subjective decision processes, sensitivity analysis, information about the evaluation criteria's implicit weights, and better understanding and participation among the members of the decision making group and, hence, a commitment to the chosen alternative (Shang, 1993).

Although AHP is a popular and useful method, it has several shortcomings, and some modifications have been suggested to improve this approach. Firstly, instead of using an additive scale ranging from 1 to 9, several alternative scales exist. One of the most common scales is the geometric scale (Lootsma, 1999). Another improvement is the implementation of a method for priority estimation, proposed by Saaty (1980), called the eigenvector technique.

The most controversial issue in the use of AHP is the rank reversal phenomenon, where the ranking of alternatives determined by AHP may be altered by the addition of another alternative for consideration. To prevent this problem, the concept of absolute measurement and the multiplicative variant of AHP can be used (Saaty, 1987). Another criticism is that AHP is not an axiomatic framework. However, Saaty (1986) has provided the necessary axioms that pertain to reciprocal comparisons, homogeneity, independence, and expectations.

The purpose of using the AHP method in this study is to obtain the weighted values that indicate the relative importance of the local governments' alternative for each criterion. At each level, the participants are asked to determine a comparison matrix by comparing pairs of criteria where the alternatives at the lowest level are compared against the standards that are established by the participants. More alternatives make the rating method more convenient. An analytic focus on the rating method enables decision-makers to easily evaluate a large number of alternatives. In the AHP method, an element is compared against an ideal property, and generally, only the final alternatives are absolutely measured. The AHP approach is attractive because it has been shown to be robust and consistent (Ertay et al., 2006).

The robustness can be verified by a sensitivity analysis of the weights. In other words, robustness is related to the sensitivity of the eigenvector, which computes the relevant rankings according to the evaluation criteria. One problem is the sensitivity of the weights given by eigenvector components to slight changes in the judgment values. Clearly, it is desirable that the weights not fluctuate widely with small changes in judgment. In this study, the Expert Choice package program is used for the sensitivity analysis of the pair-wise comparison of model alternative layouts. Details of the analysis are provided in Section 4.2.

If A is a Matrix as follows:

$$A = [a_{ij}] = \begin{pmatrix} w_1/w_1 w_1/w_2 \ldots . w_1/w_n \\ w_2/w_1 w_2/w_2 \ldots . w_2/w_n \\ \vdots \\ \vdots \\ w_n/w_1 w_n/w_2 \ldots . w_n/w_n \end{pmatrix},$$

then the matrix formula of eigenvector X is:

$$AX = \lambda X,$$

λ is used to indicate the eigenvalue.

After rearrangement, we obtain the matrix formula

$$(A - \lambda I)X = 0.$$

Another critical issue of AHP is consistency, which can be verified using the consistency ratio. For example, for consistency to be found, if $a_{ij} = 2$, $a_{jk} = 3$, then a_{ik} must be equal to 6. AHP does not require that judgments be consistent or even transitive, since the judgments are totally random in nature. Here, the important point is that the consistency of a matrix of such random judgments should be worse than that of a matrix of informed judgments. This measure can be used to compare and evaluate the consistency of informed judgments.

The consistency index (CI) of a matrix of comparisons is given by $CI = (\lambda_{max} - n)/(n - D1)$. Here, λ_{max} is the maximum eigenvalue, and n is the size of the matrix. The consistency ratio (CR) is obtained by determining the CI ratio and the random index (RI). DeSchutter developed the following relationship between the index RI and n:$RI = 1.98^{*}[(n - D2)/n]$ where 1.98 is the average value of the ratio of each value computed from $n = 3$ to 15, divided by $(n - D2)/n$ for the corresponding value of n (Saaty, 1994).

3.4. DEA evaluation method

DEA is a popular mathematical programming methodology based on the Efficiency Frontier. It has been successfully employed to study the comparative performance of units that consume similar inputs and produce similar outputs. These units are generally referred to as DMUs. When assessing the performance of government economic development, DEA combines the performances of governments in terms of several desirable and undesirable attributes into a single scalar measure, called the efficiency score. An efficiency score of unity indicates the highest values of desirable attributes and the lowest values of undesirable attributes. An efficiency score of less than one is considered as sub-optimal for a given set of attributes. Two assumptions can be made while computing efficiency scores using DEA, namely, constant returns to scale (CRS) and variable returns to scale (VRS). The assumption of CRS is said to prevail when an increase in all inputs (i.e., an increase in terms of undesirable attributes) by 1% leads to an increase in all outputs (i.e., an increase in terms of desirable attributes) by 1%. The VRS assumption prevails when the CRS assumption is not satisfied. It has been shown that DEA efficiency scores computed with the CRS assumption (hereafter, called CRS efficiency scores) are less than or equal to the corresponding VRS efficiency scores, due to the difference in scale size of DMUs. The VRS efficiency of a DMU measures only technical efficiency, while CRS efficiency accounts for both technical efficiency and efficiency loss when the DMU does not operate in its most productive scale size. The ratio of CRS to VRS scores is called the scale efficiency. The scale efficiency of a DMU operating in its most productive size is thus 1. Before detailing our study, we discuss the advantages of using DEA for a comparative performance analysis of the governments concerned.

3.5. Radial model with or without input

Lovell and Pastor (1999) proposed the Radial DEA model without input or without output. They developed four models: (1) a CCR model without input or output that was shown to be meaningless, (2) an output-oriented (input-oriented) CCR model with a single constant input (output), (3) a BCC model without input (or without output), and (4) a new formulation of the BCC model, which was shown to be completely applicable.

This study uses the third and fourth Radial DEA models to analyze the relevant data. The third model shows that an output-oriented (input-oriented) BCC model with a single constant input (output) is equivalent to an output-oriented (input-oriented) BCC model without inputs (outputs). The final formulation of the envelopment problem for an output-oriented BCC model without input is as follows:

$$\begin{aligned} \max_{\varphi,\lambda} \quad & \phi \\ \text{s.t.} \quad & Y\lambda \geqslant \phi Y_o, \\ & e^T\lambda = 1, \\ & \lambda \geqslant 0_n. \end{aligned}$$

A complete and new formulation of a BCC model with input is as follows:

$$\begin{aligned} \max_{\varphi,\lambda} \quad & \phi \\ \text{s.t.} \quad & Y\lambda \geqslant \phi Y_o, \\ & X\lambda \leqslant X_o, \\ & e^T\lambda = 1, \\ & \lambda \geqslant 0_n. \end{aligned}$$

Since $\psi \leqq 1$, we can consider a new variable $\theta = 1/\psi$. The substitution of θ for ψ in the BCC envelopment problem yields:

$$\begin{aligned} \min_{,\theta,\lambda} \quad & \theta \\ \text{s.t.} \quad & Y\lambda \geqslant (1/\theta) Y_o, \\ & X\lambda \leqslant X_o, \\ & e^T\lambda = 1, \\ & \lambda \geqslant 0_n. \end{aligned}$$

3.6. Time series analysis-MPI (malmquist productivity index)

In addition to the static performance result, in this study, we also analyzed dynamic trend performance over several years. WA and MPI are popular approaches (Fare et al., 1994). Here, the MPI method is used to understand technological practice trends in local Chinese governments, as well as changes in the efficiency of the technologies during two different time periods. The MPI approach is better for time series analysis. DEA is used to determine the efficiency frontier of a specific period. MPI links the result of the DEA analysis to extend the study period and provides a comparison of the economic performance.

The output-oriented MPI is defined as follows:

$$\mathrm{MPI}_t^{t+1}(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \times \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)}\right]^{1/2},$$

D^t is a *distance function* that measures the efficiency of the conversion of inputs x^t to outputs y^t in the period t, so if there is a technological change in period $(t+1)$, then $D^{t+1}(x^t, y^t)$ is the efficiency of conversion of the input during time t, to the output during the period $t \neq D^t(x^t, y^t)$. The MPI is a geometric average of the efficiency and technology changes in the two periods being considered. It can be written as:

$$\begin{aligned} \mathrm{MPI}_t^{t+1}(x^{t+1}, y^{t+1}, x^t, y^t) \quad &= \quad \left[\frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)}\right]^{1/2} \quad \times \quad \left[\frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)}\right]^{1/2}, \\ \text{or} \quad & \\ \mathrm{MPI} \quad &= \quad \mathrm{TEC} \quad \times \quad \mathrm{TC}, \end{aligned}$$

where TEC is the technical efficiency change and TC is the technology change. TEC measures the change in the CRS technical efficiency from t to $t+1$. If TEC-1, there is an increase in the technical efficiency of the conversion of inputs to outputs. TC represents the average technological change between the two periods. In addition to MPI, TEC, and TC, other efficiency changes over time may be defined. For example, the VRS efficiency change for a government can be calculated as the ratio of its VRS efficiency for period $t+1$ to that for t (Fare et al., 1994).

4. Empirical study and illustration

4.1. Empirical design

There are ten variables in this study, two qualitative variables used for AHP analysis and the others for DEA. AHP is a multi-criteria decision-making method that uses hierarchical or network structures to represent a decision problem and then develops priorities for the alternatives based on the decision-maker judgments throughout the system. The hierarchical structure of the two variables is given in Section 4.2.1.

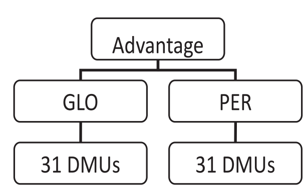
DEA is a popular mathematical programming methodology based on the efficiency frontier, and both CCR and BCC models must consider whether variables attribute are inputs or outputs. This study measures ten variables that are used for evaluating economic performance. GLO, PER, GEX, FDI and EPS are inputs, while the other five variables are outputs, as indicated in Fig. 1 and Table 2. The 31 local governments designated as DMUs are important and are presented in Table 3, which also provides the alternatives for the study.

4.2. AHP analysis

Ten executive managers working in the Taiwanese Tooling Design and Manufacturing Enterprise Group were invited to participate in this study. All of them have been working over 5 years at different factory in China, four were at Nanjing factory, three were at Tianjin factory, while the remaining in Taiwan. Before evaluating, we explained the meaning of AHP as well as instructed the detail rules that how to proceed with this study separately to participants, afterward each participant was asked to develop a comparison matrix by comparing pairs of criteria, so that the alternatives at the lowest level are compared against the standards established by the AHP method. For the purpose of ensuring that comparing pairs were valid and objective, we deleted the unreasonable pair value of each participant by CI index, then averaged and analyzed evaluating comparison pairs to obtain synthesis weights by AHP method. Since the GLO and PER attributes are qualitative, AHP pair comparisons must be used to obtain the DMU weights. This is presented in Section 4.2.2.

Both approaches will be integrated by converting the variables and local weights of the AHP analysis into input variables and by combining this with the original data in the DEA analysis.

4.2.1. Hierarchy structure



4.2.2. Weight value of AHP

AHP analysis can be used to obtain the variable weights and to indicate the relative importance of the local government alternatives for each criterion. At each level, the participants are asked to determine a comparison matrix by comparing pairs of criteria. An increased number of alternatives make the rating method more convenient. The analytic focus of the rating method enables decision-makers to easily evaluate a large number of alternatives. In the AHP method, an element is compared against an ideal property, and only the final alternatives are measured. This study utilizes the Expert Choice software package to measure the comparison matrix, and the results are provided in Fig. 2.

4.2.3. Sensitivity analysis and consistency index

Sensitivity analysis is used to understand major trends, and the final results (Fig. 3) indicate that east district provinces in China

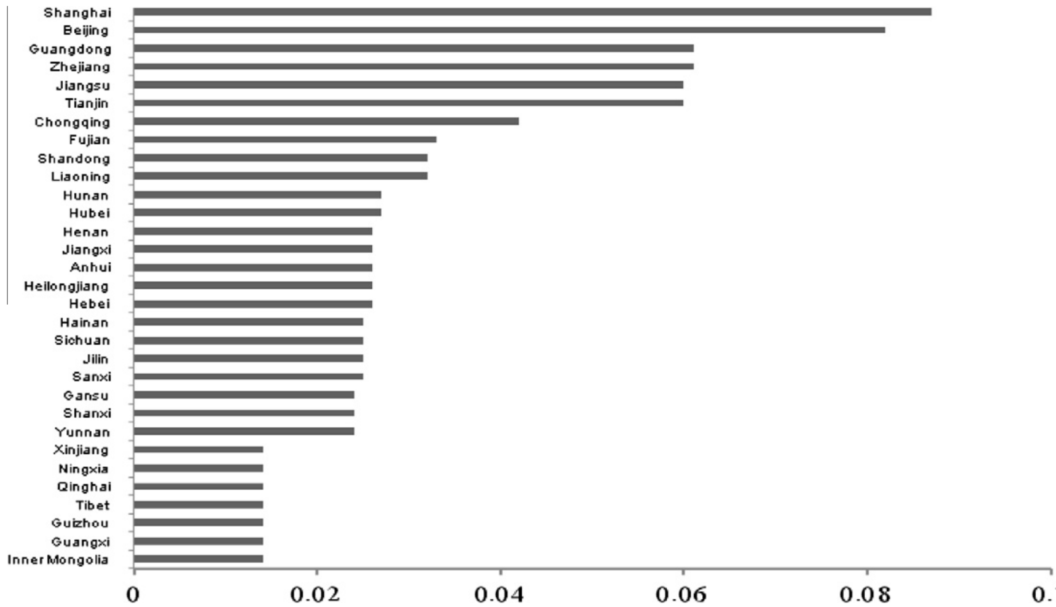


Fig. 2. Synthesis weights and ranking of DMUs.

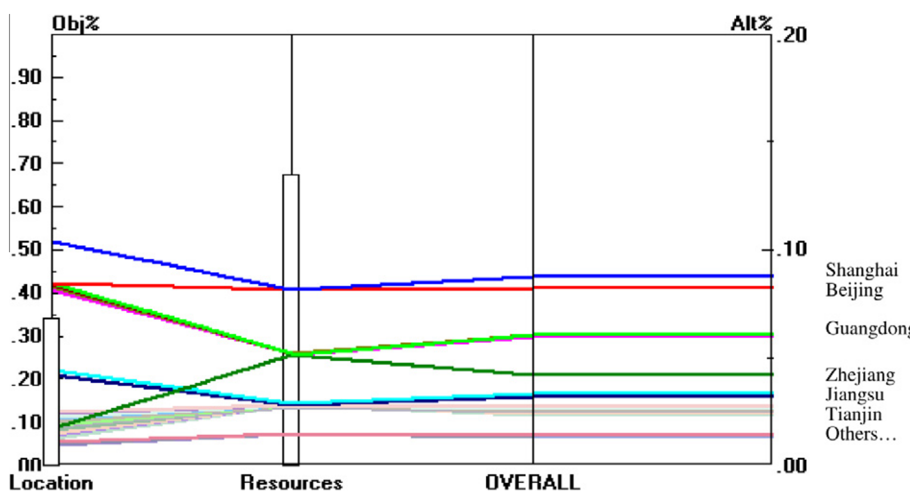


Fig. 3. Performance sensitivity diagram.

have more advantages than the central and west districts, in regards to geography location and politic and economic resource support. In addition Shanghai and Beijing are the most able to obtain resource support from the central government, as these two municipalities are a priority regardless of the FDI. This conclusion is coincident with prior conceptions.

Additionally, the CI is a very important process that clarifies and verifies the judgment of all participants. The study determined that both CI variable values are less than 0.01; this means that all participant comparisons can be considered rational.

4.3. DEA model analysis

Before using the DEAP2.1-XP and Frontier Analyst 4.0 software package, we performed a correlation to determine any significant effects between input and output variables. After this, the CRS and VRS efficiencies were used to rank the economic performance of local governments under different conditions (such as without and with input), in order to understand the effects of different situations like geography location, execution of local governments, foreign direct investments, politic and economic support from the central government, etc. completed DEA model analysis with inputs is commonly used to evaluate the efficiency frontier between inputs and outputs; for a DEA model without inputs, the effectiveness of the model is evaluated without concern for input requirements; in this study, we also analyze DEA model with quantitative input variables excluding GLO and PER to understand the cause and effect of quantitative attribution of input variables and compare with completed DEA model mentioned above.

MPI was used to analyze the economic growth rate of each DMU and to rank their economic performance. In general, it is very important to locate optimum investment locations in China using different models and approaches, and results obtained with or without inputs determine which local governments have the best performance. A detailed illustration of the above study follows in Sections 4.3.2–4.3.6.

4.3.1. Data collection for DEA analysis

DEA data was collected from "China's Economic and Trade Yearbook" (2006, 2007), which is a resource providing abundant and detailed information. At first, we categorized information according to characteristics of different variables, then integrated GLO and PER local weights analyzed by AHP approach (see Fig. 2) to be used as input for the 31 DMUs in 2005 and 2006 for DEA analysis. The measurement of the input and output variables are not similar, due to their different characteristics. Input data of synthesis weights are qualitative and arbitrarily judged, with the percentage used as the common measuring unit; the other input data included GEX (government execution), FDI (foreign direct investment) and EPS (new enterprises) indicates how many new enterprises are established within a specific period and demonstrates the effectiveness of local government business recruitment are quantitative used to be the measurable variable of DEA analysis. Output data are all quantitative, and common variables used to indicate the DMU economic performance include GNP, which is the most important in economic performance, is expressed in billion/10 RMBs; IMP (Import Dollars) and EXP (Export Dollars) both indicate the performance of international trade and are expressed in billion/10 of dollars; FIN (Financial Income) is an indicator of the local government income, which is a very important index of government management, and uses billion/10 RMBs as its unit; FAM (Family Income) indicates the income per family, which is another indicator of government economic performance, and uses RMBs as the unit.

4.3.2. Correlation analysis

The correlation analysis between inputs and outputs is used to identify any cause and effect relationship between input and output variables. In this study, we assume that $p \geqq 0.05$ is not significant, $p \leqq 0.05$ is significant, $p \leqq 0.01$ is more significant, and $p \leqq 0.001$ is the most significant. After checking p value of Tables 4 and 5, finds that most correlation coefficients are strong and have a p value less than 0.05, it indicates that all results of the correlation analysis are improved. The meaning of this phenomenon is that all output variables will be affected by the input variables, and the relationship between cause and effect is significant. This also indicates that the DEA model performance is beneficial. The variations between 2005 and 2006 are not significant, and the data for each year is consistent and stable as expected. In summary, the DEA model analysis is shown to produce satisfactory results.

Table 4
2005 Correlation between DEA inputs and outputs.

Input	Output				
	GNP	IMP	EXP	FIN	FAM
GLO	.647([c]) .000 31	.808([c]) .000 31	.753([c]) .000 31	.842([c]) .000 31	.924([c]) .000 31
PER	.447([a]) .012 31	.700([c]) .000 31	.552([b]) .001 31	.702([c]) .000 31	.888([c]) .000 31
GEX	.503([b]) .004 31	.697([c]) .000 31	.591([c]) .000 31	.732([c]) .000 31	.921([c]) .000 31
FDI	.894([c]) .000 31	.837([c]) .000 31	.924([c]) .000 31	.863([c]) .000 31	.520([c]) .003 31
EPS	.919([c]) .000 31	.679([c]) .000 31	.814([c]) .000 31	.870([c]) .000 31	.614([c]) .000 31

[a] $p \leqq 0.05$.
[b] $p \leqq 0.01$.
[c] $p \leqq 0.001$.

Table 5
2006 Correlation between DEA inputs and outputs.

Input	Output				
	GNP	IMP	EXP	FIN	FAM
GLO	.639([c]) .000 31	.812([c]) .000 31	.747([c]) .000 31	.830([c]) .000 31	.931([c]) .000 31
PER	.436([a]) .014 31	.710([c]) .000 31	.544([c]) .002 31	.685([c]) .000 31	.899([c]) .000 31
GEX	.499([b]) .004 31	.693([c]) .000 31	.573([c]) .001 31	.711([c]) .000 31	.928([c]) .000 31
FDI	.896([c]) .000 31	.816([c]) .000 31	.917([c]) .000 31	.876([c]) .000 31	.535([c]) .002 31
EPS	.911([c]) .000 31	.642([c]) .000 31	.791([c]) .000 31	.864([c]) .000 31	.591([c]) .000 31

[a] $p \leqq 0.05$.
[b] $p \leqq 0.01$.
[c] $p \leqq 0.001$.

4.3.3. DEA model analysis without input

In this section, we will overviews the use of the Radial DEA model of Knox et al. (1999) without inputs. It differs from the DEA model with inputs. By removing inputs from the model, a constraint formula with input variables as $X\lambda \leqq X_o$ can be developed, it also means that the inputs are cognized no difference. A CCR model without inputs is meaningless, and this model is used for the BCC model. This study assumes that variables like geographical location and central government economic support can be compared on an equivalent basis. In actuality, support from the Chinese central government is inherently unequal; the interior provinces have always lacked central government political and economic support, which limits the entrance of FDI, In addition, international trade activity is limited as a result of higher transportation costs, etc. A DEA model without inputs allows for each of the local governments to be evaluated solely on their own merits, without outside input. This was performed for two years of data (2005, 2006), giving results for the VRS efficiency, scale efficiency, and ranking series, as shown in Table 6.

Table 6 shows that the CRS and VRS efficiencies are equivalent. Since the CCR model is meaningless as mentioned above, the DEAP2.1-XP software was used to generate CRS efficiency values as VRS. All scaled efficiency values (CRS/VRS) for the DMUs were equal to 1, suggesting that there was little difference between them. A simple survey of the VRS efficiency shows that a DMU value of 1 indicates a better technical efficiency, and values smaller than 1 correspond to a lower technical efficiency. A ranking of all DMUs by this criteria results in the sequence presented in Table 6. East district provinces and municipalities, such as Shanghai, Jiangsu, Zhejiang, Shandong, and Guangdong generally exhibited the best technical efficiency; DMUs in the central and west districts had a lower technical efficiency, with values of less than 0.5 for some governments of these districts. This indicates a very inefficient economic performance. This result is reflected in certain social aspects in China, such as the continuing increase of the Gini coefficient and the serious gap between the rich and poor. This economic inefficiency is an important contributor in the current social problems.

4.3.4. DEA model analysis with all inputs

This section details how the full DEA model with inputs is used to measure scale efficiency, compare productivity, and evaluate the

Table 6
Efficiency scores and rankings for 2005 and 2006, excluding input.

No.	DMUs	CRS efficiency		VRS efficiency		Scale efficiency		Return of scale		Ranking	
		2005	2006	2005	2006	2005	2006	2005	2006	2005	2006
1	Beijing	0.954	0.983	0.954	0.983	1.0	1.0	–	–	3	3
2	Tianjin	0.678	0.691	0.678	0.691	1.0	1.0	–	–	7	7
3	Liaoning	0.537	0.552	0.537	0.552	1.0	1.0	–	–	12	12
4	Shanghai	1.000	1.000	1.000	1.000	1.0	1.0	–	–	1	1
5	Jiangsu	0.829	0.862	0.829	0.862	1.0	1.0	–	–	5	5
6	Zhejiang	0.949	0.962	0.949	0.962	1.0	1.0	–	–	4	4
7	Fujian	0.668	0.674	0.668	0.674	1.0	1.0	–	–	8	8
8	Shandong	0.828	0.843	0.828	0.843	1.0	1.0	–	–	6	6
9	Guangdong	1.000	1.000	1.000	1.000	1.0	1.0	–	–	1	1
10	Hebei	0.566	0.579	0.566	0.579	1.0	1.0	–	–	9	9
11	Sanxi	0.478	0.485	0.478	0.485	1.0	1.0	–	–	20	19
12	Jilin	0.466	0.473	0.466	0.473	1.0	1.0	–	–	22	22
13	Heilongjiang	0.464	0.464	0.464	0.464	1.0	1.0	–	–	24	23
14	Anhui	0.471	0.488	0.471	0.488	1.0	1.0	–	–	21	17
15	Jiangxi	0.462	0.462	0.462	0.462	1.0	1.0	–	–	25	24
16	Henan	0.552	0.568	0.552	0.568	1.0	1.0	–	–	10	10
17	Hubei	0.502	0.507	0.502	0.507	1.0	1.0	–	–	15	14
18	Hunan	0.536	0.537	0.536	0.537	1.0	1.0	–	–	13	13
19	Inner Mongolia	0.490	0.501	0.490	0.501	1.0	1.0	–	–	19	15
20	Guangxi	0.498	0.479	0.498	0.479	1.0	1.0	–	–	16	21
21	Chongqing	0.549	0.560	0.549	0.560	1.0	1.0	–	–	11	11
22	Sichuan	0.495	0.501	0.495	0.501	1.0	1.0	–	–	18	15
23	Guizhou	0.437	0.441	0.437	0.441	1.0	1.0	–	–	29	28
24	Yunnan	0.497	0.487	0.497	0.487	1.0	1.0	–	–	17	18
25	Tibet	0.506	0.433	0.506	0.433	1.0	1.0	–	–	14	30
26	Shanxi	0.444	0.448	0.444	0.448	1.0	1.0	–	–	27	26
27	Gansu	0.434	0.432	0.434	0.432	1.0	1.0	–	–	31	31
28	Qinghai	0.432	0.435	0.432	0.435	1.0	1.0	–	–	30	29
29	Ningxia	0.434	0.444	0.434	0.444	1.0	1.0	–	–	28	27
30	Xinjiang	0.429	0.483	0.429	0.483	1.0	1.0	–	–	23	20
31	Hainan	0.436	0.455	0.436	0.455	1.0	1.0	–	–	26	25
	Mean	0.581	0.588	0.581	0.588	1.0	1.0				

Table 7
Efficiency scores and rankings for 2005 and 2006, including all inputs.

No.	DMUs	CRS efficiency		VRS efficiency		Scale efficiency		Return of scale		Ranking	
		2005	2006	2005	2006	2005	2006	2005	2006	2005	2006
1	Beijing	1.000	1.000	1.000	1.000	1.000	1.000	–	–	1	1
2	Tianjin	0.809	0.853	0.882	0.903	0.918	0.944	Drs.	Drs.	29	31
3	Liaoning	1.000	1.000	1.000	1.000	1.000	1.000	–	–	1	1
4	Shanghai	1.000	1.000	1.000	1.000	1.000	1.000	–	–	1	1
5	Jiangsu	0.872	0.879	0.874	0.880	0.997	0.999	Drs.	Irs	19	22
6	Zhejiang	1.000	1.000	1.000	1.000	1.000	1.000	–	–	1	1
7	Fujian	0.992	1.000	1.000	1.000	0.992	1.000	Drs.	–	21	1
8	Shandong	1.000	1.000	1.000	1.000	1.000	1.000	–	–	1	1
9	Guangdong	1.000	1.000	1.000	1.000	1.000	1.000	–	–	1	1
10	Hebei	1.000	1.000	1.000	1.000	1.000	1.000	–	–	1	1
11	Sanxi	0.989	1.000	1.000	1.000	0.989	1.000	Drs.	–	22	1
12	Jilin	0.843	0.840	0.883	0.881	0.954	0.954	Drs.	Drs.	28	30
13	Heilongjiang	1.000	1.000	1.000	1.000	1.000	1.000	–	–	1	1
14	Anhui	0.896	0.900	0.900	0.903	0.996	0.996	Drs.	Drs.	20	23
15	Jiangxi	0.814	0.819	0.840	0.847	0.970	0.967	Drs.	Drs.	26	28
16	Henan	1.000	1.000	1.000	1.000	1.000	1.000	–	–	1	1
17	Hubei	0.890	0.884	0.901	0.891	0.988	0.992	Drs.	Drs.	23	24
18	Hunan	0.928	0.925	0.944	0.935	0.983	0.989	Drs.	Drs.	25	25
19	InnerMongolia	1.000	1.000	1.000	1.000	1.000	1.000	–	–	1	1
20	Guangxi	1.000	1.000	1.000	1.000	1.000	1.000	–	–	1	1
21	Chongqing	0.909	0.977	1.000	1.000	0.909	0.977	Drs.	Drs.	30	26
22	Sichuan	1.000	1.000	1.000	1.000	1.000	1.000	–	–	1	1
23	Guizhou	1.000	1.000	1.000	1.000	1.000	1.000	–	–	1	1
24	Yunnan	1.000	1.000	1.000	1.000	1.000	1.000	–	–	1	1
25	Tibet	1.000	1.000	1.000	1.000	1.000	1.000	–	–	1	1
26	Shanxi	0.959	0.943	0.990	0.969	0.969	0.973	Irs	Irs	27	27
27	Gansu	0.901	0.957	1.000	1.000	0.901	0.957	Irs	Irs	31	29
28	Qinghai	0.870	1.000	0.870	1.000	1.000	1.000	–	–	1	1
29	Ningxia	0.869	1.000	0.870	1.000	1.000	1.000	–	–	1	1
30	Xinjiang	1.000	1.000	1.000	1.000	1.000	1.000	–	–	1	1
31	Hainan	0.957	1.000	0.972	1.000	0.984	1.000	Irs	–	24	1
	Mean	0.952	0.967	0.965	0.974	0.985	0.992				

output-based efficiency. Therefore, this model is also called the output-oriented efficiency model. The study assumed that all local governments had an unequal amount of resources and support from the central government, which covers differences due to location and political/economic support. Superior performance is a result of abundant support from the government and location advantage. Local governments like Shanghai and Beijing obtain resources from the Chinese central government that greatly exceed that received by the western poor areas. The result of this inherent inequality is that few FDIs will become involved in these poorer interior provinces, and international trade activity becomes scarce. A further problem is that increased transportation costs to these places have a further economic impact. The DEA model accounts for these inputs factors so that each local government can be evaluated under equal conditions. The DEA analysis was performed over 2005 and 2006, giving results for the VRS efficiency, scale efficiency, and rankings, as shown in Table 7.

The results in Table 7 differ from those in Table 6, indicating a clear distinction between CRS and VRS efficiency scores, since the CCR model is now meaningful. Even though the value of scale efficiency (CRS/VRS) of the DMUs is 1, 13 DMUs in 2005 and 10 DMUs in 2006 are less than 1. A review of the efficiency scores and ranking by scale efficiency gives further evidence of a deviation from that of Section 4.3.3 (a model without inputs), which showed that the local governments did not vary greatly on efficiency. However, when accounting for input factors, the change in the ranking is diminutive and gives the positive result, as now most of the west district governments have a low ranking when ignore inputs factor, but when inputs were adopted to analyze with completed DEA model, the differentiation of efficiency was small (see Tables 6 and 7). This finding is very important for evaluating economic performance, because many factors impact poor economies; the most important causes are a lack of support from the central government and location. When these factors are taken into account in the analysis, the economic performance results appear to be counterintuitive.

4.3.5. DEA model analysis with quantitative inputs

The Section 4.3.4 details how the DEA model with all inputs including qualitative and quantitative variables used to analyze efficiency, in this section, we remove qualitative variables from completed model and details how the DEA model with quantitative inputs only is used to measure scale efficiency, the purpose is to explore and compare results of different DEA model as well as to understand the consistence by AHP analysis. Consequently, we find that most of local governments' CRS and VRS technical efficiency scores are very close to mentioned above except Liaoning, Guangxi and Sichuan as indicated in Table 8, furthermore, the scale efficiency scores of this model is also approach all inputs model. The meanings of this result are worth exploring because it overturned our cognition and the results are contrary to expectations. Actually, the results are better than expected and the variations are a scarcely perceptible movement. Even though the efficiency scores of Liaoning, Guangxi and Sichuan are bigger variation than other local governments, these local governments are still keep economic performance on a regular basis. In generally, this finding is very important for evaluating economic performance, because inputs factors are not affected by variables characteristic. Meanwhile, in this study, we can approve that the results of AHP analysis also impact poor DEA model efficiency.

4.3.6. MPI for productivity index

The results of this study of performance for 31 DMUs in 2005 and 2006 are presented in Tables 6–8. The MPI and other indices for the 2005 $\sim$ 2006 period are shown in Table 9. Interestingly, the MPI for the 25th DMU Tibet is 6.122 and the 28th DMU Qinghai

Table 8
Efficiency scores and rankings for 2005 and 2006, including quantitative inputs.

No.	DMUs	CRS efficiency		VRS efficiency		Scale efficiency		Return of scale		Ranking	
		2005	2006	2005	2006	2005	2006	2005	2006	2005	2006
1	Beijing	1.000	1.000	1.000	1.000	1.000	1.000	–	–	1	1
2	Tianjin	0.808	0.811	0.820	0.816	0.986	0.995	Drs.	Irs	27	21
3	Liaoning	0.832	0.864	0.841	0.877	0.989	0.985	Irs	Irs	24	23
4	Shanghai	1.000	1.000	1.000	1.000	1.000	1.000	–	–	1	1
5	Jiangsu	0.872	0.878	0.874	0.880	0.997	0.998	Drs.	Irs	15	18
6	Zhejiang	1.000	1.000	1.000	1.000	1.000	1.000	–	–	1	1
7	Fujian	0.909	0.901	0.919	0.925	0.989	0.975	Irs	Irs	24	25
8	Shandong	1.000	1.000	1.000	1.000	1.000	1.000	–	–	1	1
9	Guangdong	1.000	1.000	1.000	1.000	1.000	1.000	–	–	1	1
10	Hebei	0.996	1.000	1.000	1.000	0.996	1.000	Drs.	–	18	1
11	Sanxi	0.929	1.000	0.932	1.000	0.996	1.000	Drs.	–	18	1
12	Jilin	0.819	0.807	0.848	0.829	0.965	0.974	Drs.	Drs.	20	26
13	Heilongjiang	1.000	1.000	1.000	1.000	1.000	1.000	–	–	1	1
14	Anhui	0.889	0.842	0.889	0.876	1.000	0.960	–	Irs	1	29
15	Jiangxi	0.793	0.751	0.794	0.777	0.999	0.967	Irs	Irs	14	28
16	Henan	1.000	1.000	1.000	1.000	1.000	1.000	–	–	1	1
17	Hubei	0.874	0.865	0.880	0.865	0.993	1.000	Drs.	–	22	1
18	Hunan	0.901	0.867	0.910	0.893	0.990	0.971	Irs	Irs	23	27
19	InnerMongolia	1.000	1.000	1.000	1.000	1.000	1.000	–	–	1	1
20	Guangxi	0.922	0.903	0.925	0.904	0.997	0.998	Irs	Irs	15	18
21	Chongqing	0.890	0.951	0.894	0.954	0.995	0.997	Irs	Drs.	20	20
22	Sichuan	0.914	0.899	0.948	0.982	0.964	0.916	Irs	Irs		31
23	Guizhou	1.000	0.982	1.000	1.000	1.000	0.982	–	Irs	1	24
24	Yunnan	1.000	1.000	1.000	1.000	1.000	1.000	–	–	1	1
25	Tibet	1.000	1.000	1.000	1.000	1.000	1.000	–	–	1	1
26	Shanxi	0.938	0.919	0.961	0.924	0.976	0.995	Irs	Drs.	29	21
27	Gansu	0.879	0.926	1.000	1.000	0.879	0.926	Irs	Irs	31	30
28	Qinghai	0.857	1.000	0.867	1.000	0.988	1.000	Drs.	–	26	1
29	Ningxia	0.760	1.000	0.802	1.000	0.948	1.000	Drs.	–	30	1
30	Xinjiang	1.000	1.000	1.000	1.000	1.000	1.000	–	–	1	1
31	Hainan	0.957	1.000	0.972	1.000	0.984	1.000	Irs	–	28	1
	Mean	0.927	0.941	0.938	0.952	0.988	0.988				

Table 9
Malmquist productivity index analysis over 2005 ∼ 2006.

No.	DMUs	Change in Total Technical efficiency.TEC		Change in technical efficiency (TC)		Malmquist productivity index (MPI)		Change in pure technical efficiency		Change in scale efficiency	
		Without inputs	With inputs	Without inputs	With inputs	Without inputs	With inputs	Without inputs	With inputs	Without inputs	With inputs
1	Beijing	1.120	1.169	1.030	1.000	1.154	1.169	1.030	1.000	1.000	1.000
2	Tianjin	1.109	1.030	1.019	1.054	1.130	1.086	1.019	1.024	1.000	1.029
3	Liaoning	1.111	1.163	1.028	1.000	1.142	1.163	1.028	1.000	1.000	1.000
4	Shanghai	1.117	1.143	1.000	1.000	1.117	1.143	1.000	1.000	1.000	1.000
5	Jiangsu	1.117	1.071	1.040	1.008	1.161	1.079	1.040	1.006	1.000	1.002
6	Zhejiang	1.111	1.077	1.014	1.000	1.127	1.077	1.014	1.000	1.000	1.000
7	Fujian	1.111	1.075	1.009	1.008	1.122	1.084	1.009	1.000	1.000	1.008
8	Shandong	1.172	1.162	1.018	1.000	1.192	1.162	1.018	1.000	1.000	1.000
9	Guangdong	1.187	1.155	1.000	1.000	1.187	1.155	1.000	1.000	1.000	1.000
10	Hebei	1.111	1.120	1.023	1.000	1.137	1.120	1.023	1.000	1.000	1.000
11	Shanxi	1.109	1.319	1.015	1.011	1.125	1.334	1.015	1.000	1.000	1.011
12	Jilin	1.109	1.057	1.015	0.997	1.125	1.054	1.015	0.997	1.000	1.000
13	Heilongjiang	1.111	1.004	1.000	1.000	1.112	1.004	1.000	1.000	1.000	1.000
14	Anhui	1.111	1.062	1.036	1.004	1.152	1.066	1.036	1.003	1.000	1.000
15	Jiangxi	1.109	1.039	1.000	1.006	1.109	1.045	1.000	1.008	1.000	0.997
16	Henan	1.111	1.103	1.030	1.000	1.145	1.103	1.030	1.000	1.000	1.000
17	Hubei	1.111	1.076	1.011	0.993	1.124	1.068	1.011	0.989	1.000	1.004
18	Hunan	1.111	1.046	1.001	0.997	1.113	1.043	1.001	0.991	1.000	1.006
19	InnerMongolia	1.109	1.046	1.023	1.000	1.134	1.046	1.023	1.000	1.000	1.000
20	Guangxi	1.109	1.112	0.962	1.000	1.066	1.112	0.962	1.000	1.000	1.000
21	Chongqing	1.109	1.021	1.019	1.075	1.130	1.097	1.019	1.000	1.000	1.075
22	Sichuan	1.111	1.197	1.013	1.000	1.126	1.197	1.013	1.000	1.000	1.000
23	Guizhou	1.109	1.000	1.009	1.000	1.119	1.000	1.009	1.000	1.000	1.000
24	Yunnan	1.109	1.108	0.980	1.000	1.087	1.108	0.980	1.000	1.000	1.000
25	Tibet	1.109	6.122	0.855	1.000	0.948	6.122	0.855	1.000	1.000	1.000
26	Shanxi	1.109	1.091	1.011	0.984	1.120	1.073	1.011	0.979	1.000	1.004
27	Gansu	1.109	1.000	0.995	1.062	1.103	1.062	0.995	1.000	1.000	1.062
28	Qinghai	1.109	2.322	1.008	1.149	1.117	2.668	1.008	1.149	1.000	1.000
29	Ningxia	1.109	1.574	1.023	1.150	1.134	1.811	1.023	1.150	1.000	1.000
30	Xinjiang	1.109	1.075	1.127	1.000	1.249	1.075	1.127	1.000	1.000	1.000
31	Hainan	1.109	1.141	1.043	1.045	1.156	1.193	1.043	1.028	1.000	1.016
	Mean	1.115	1.198	1.011	1.017	1.127	1.218	1.011	1.010	1.000	1.007

is 2.668 in DEA model with inputs. Both numbers are larger, as compared with the other DMUs. It seems irrational, because Tibet and Qinghai is located in west China and has few resources, industries, support, and foreign investment. They only have the most land but a low population, so one of its key industries is tourism. Although the possibility exists that incorrect information was sent to the relevant department, but a check on this has yielded no abnormal results. Meanwhile we find that due to the smaller value of input and output variables compared with others provinces, result in the quantitative analysis is more sensitive and affect the MPI value of both provinces to be larger.

Table 9 indicates most DMUs MPI value is larger than 1, which suggests that the economic growth of China is in a favorable situation. A thorough check of the data shows that the advantage is not significant in the all local governments except Tibet and Qinghai which suggests that the economic growth rates are better than the others. Also we find whatever DEA model be used the MPIs value of local governments are in close vicinity which ranged from 1.000 to 1.200 in Table 9, the meanings of this results are that most of DMUs have poor deviation of economic growth rate excluded Tibet and Qinghai are higher mentioned as above. Furthermore, compare the results of different districts indicate that after discounting as well as taking into consideration the advantages of location and political connections, since the average MPIs value of each districts are as follow when discounting concerned: the east district is 1.149; the central district is 1.125; the west district is 1.111, the east district provinces of China do not have superior economic performance or a better MPI index, when taking into counting for all inputs variables, even though the Tibet MPI value are neglected, the economic growth and performance of east district is worse than another districts. This result is seems contrary to our original hypothesis.

5. Implications

The results of our analysis have valuable policy implications for evaluating economic performance and making investment decisions in China. Additionally, there are those who are always suspicious of economic statistical reports of China. We wish to stress here that the findings of this study were made with critical thought given to the choice of variables, so the implications discussed below should be considered with this in mind.

1. The prevailing stereotype regarding the economic situation in China is that the provinces and municipalities along the coast in China are exhibiting progressive growth in economic development and are therefore rich. In some cases, this stereotype is based on fact. The AHP approach used in this study provides an understanding of this perception, indicating that most participants fall into this stereotype. However, a thorough investigation reveals that this phenomenon is exaggerated by external social factors. Our DEA analysis shows that the stereotype is not true.
2. The DEA model is a mathematical programming linear approach and can help researchers to obtain the best solution for multi-criteria decision making. This study utilizes two DEA's model, one is an analysis without inputs, while the other includes inputs. The reason for using a model without inputs is to understand the efficiency difference between the east and middle/ west districts in the absence of the disparity in resources and

support from the central government. The results clearly indicate that the east district performs better than the others, and the deviation is very large. However, considering that the east area obtains a high level of support and investment from the central government and foreign countries, the complete model with inputs shows that their efficiency values are not as high as initially perceived. Furthermore, the results even show that some middle and west local governments have higher efficiency values than those in the east. This shows that a comparison based only on the outcomes is inaccurate. Since support to the regions is unequal, and considering the nature of the conditions, the west and middle governments are remarkably effective.

3. Interestingly, this study also finds peculiar results, as the MPI value of Tibet is 6.122, which is very large. If this value is correct and if the data from the Chinese government is correct, then Tibet is one of the most economically viable regions, having almost quadrupled in growth from 2005 to 2006, which in actuality is impossible. We attribute this result in Tibet to statistical information error, or it is an aberrant result.

6. Conclusion

In this paper, the economic performance of local governments in China is evaluated by an available model. The results are useful in improving our understanding of the economy in China. Although currently known as the largest market in the world, it would appear that there is potential for even greater growth. China is a mainland, and each local government has unique features and traditions. There are many races, different languages, and different ways of thinking, so a complete understanding of the country is impossible. Therefore, this study aims to provide some basic information that allows for a better understanding of this country.

The results of this paper show that the economic performances of local governments exhibit a great divergence between different model analyses. For the DEA model that does not consider input factors, the east is the highest ranked region, while the west and central regions are ranked lower. If relevant input factors are considered, then the ranking significantly changes, and the east has a lower ranking. This means that the choice of DEA model (with or without inputs) has a significant effect on the economic conclusions drawn from a study.

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