Performance Assessment of Asian and Chinese Super Cities by means of Super-efficient DEA

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Abstract: Over the past decades, many Asian cities - especially, Chinese cities - have shared an unprecedented high degree of economic and geographic-demographic dynamics. It is noteworthy however, that cities in this region display also much heterogeneity in terms of economic performance, technological innovativeness, cultural profiles and spatial interaction. It is, therefore, interesting to develop an efficiency ranking of the multi-dimensional performance of these large cities so as to identify 'super-cities', whose (socio-)economic and cultural achievements outperform others. The first aim of this paper is now to undertake a multi-faceted performance ranking of 12 large (global) cities in the Asian region, with a special focus on Chinese large cities (Hong Kong, Shanghai and Beijing), by using of a Super-efficient DEA (Data Envelopment Analysis). In this study, we consider 3 inputs (Number of Employees, Research and Development Expenditures and Cultural Resources) and 2 outputs (GDP and Volume of Interaction). Based on a large-scale data base and our analysis results, it appears that Hong Kong, Kuala Lumpur, Bangkok, Tokyo and Singapore may be regarded as a Super-efficient Cities. It also turns out that Osaka, Shanghai, Beijing, Seoul, Fukuoka, Mumbai and Taipei manifest themselves as inefficient cities. In these inefficient cities, there is clearly scope for improvement in performance, which requires of course an efficiency enhancement strategy, depending on the choice of productive inputs and achievement levels (outputs). In our modelling approach, we employ an efficiency-improving projection model, called a Distance Friction Minimization (DFM) model in DEA. The DFM model is based on a generalized distance friction function and serves to improve the performance of a Decision-Making Unit (DMU) by identifying the most appropriate movement towards the efficiency frontier surface. To design a feasible and realistic improvement strategy for low-efficiency cities, we develop a Target-Oriented (TO) DFM model, in order to generate an appropriate efficiency-improvement projection model. The standard TO approach specifies a target-efficiency score (TES) for inefficient DMUs. Next, we also develop an objective target-setting model in our TO-DFM approach in DEA, named the Autoconfiguration Target (AT)-DFM model. This approach is able to compute an input reduction value and an output increase value in order to achieve an autoconfiguration target-efficiency score. The second aim of this paper is to apply this newly develop AT-DFM model with a fixed (or indivisible) factor (FF) reflecting more realistic circumstances and requirements in an operational strategy for a feasible efficiency improvement. The above-mentioned new AT-DFM-FF model will be applied in order to provide an efficiency-improving projection for inefficiency enhancement of several large Asian cities, especially focused on the Chinese cities of Shanghai and Beijing.

Keywords: Chinese Super Cities, Super-Efficient DEA, AT-DFM Fixed Factor model

JEL codes: R11, O18

1. Introduction: Background, Analysis Framework and Aims

Our current world is increasingly moving towards the '*urban century'*, in which the role of large urban systems is becoming more and more important. Population dynamics and movement are critical in shaping this '*New Urban World*' (Kourtit 2019). It is noteworthy that Japan is in a transition process towards a depopulating society as a result of the structural ageing process. And Korea, Thailand and even China will also become depopulating nations in the near future. Despite the resulting population decline in many countries, most cities in our world continue to grow. And most likely, Asian countries and cities will continue to be an engine of growth. In general, cities in our world tend to increase in number and in size. The unprecedented increases in urban population, in China - and in many parts of the world -, have close links with the magnetism and the economic performance of cities. In this context, urban agglomerations and metropolitan areas have become the engines of economic, technological, political and social power. Consequently, cities are not passive actors in a dynamic and open world geography. Instead, the awareness is rapidly growing that major agglomerations – especially mega-cities with more than 10 mln inhabitants – become the new '*control and command centres*' of our world (Sassen 1991). Such large urban areas become contemporaneous influential powerhouses of economic activity, in combination with their creative, cognitive and innovative ability. Their historically centripetal and centrifugal impact is now extended from their traditional hinterlands to a world-wide scale in a globalizing economy.

Over the past decades, many Asian cities - especially Chinese cities - has exhibited an unprecedented high degree of economic and geographic dynamics. Clearly, cities in the Asian region display much heterogeneity in terms of economic performance, technological innovativeness, cultural recognition and interaction. It is therefore, interesting to develop an efficiency ranking of the multi-dimensional performance of these large cities so as to identify '*Asian super-cities'*.

In recent years, many efforts have been made to create a classification or ranking of cities based on their actual performance or their perceived success (see e.g. Taylor et al. 2009, Grosveld 2002, Arribas-Bel et al. 2011; Kourtit et al. 2012). A main challenge in current empirical research is the creation of a consistent, quantitative database that is suitable for a comparative, strategic urban benchmark analysis. In the extant literature on comparisons of cities one finds a great diversity of such approaches. Urban efficiency performance has been assessed from a broad perspective based on various quantitative models (Qui, Xu and Zhang (2015), Hao, Zhu and Zhong (2015), Saaty, and Sagir (2015), Guan and Rowe (2016), Manijeh (2016)).

The measurement of urban performance calls for an appropriate methodological approach, in which the output-input ratio of cities will be interpreted as a performance measure (in economics usually called efficiency or productivity). The assessment of urban output achievement and urban input efforts is however, fraught with many operational problems. In the past decades, a very effective instrument has been developed and employed, called Data Envelopment Analysis (DEA), which is able to confront a multidimensional set of outputs with a multidimensional set of inputs (see Charnes et al. 1978). An overview can be found in Suzuki and Nijkamp (2017a)

DEA has become an established quantitative assessment tool in the evaluation literature. Already more than a decade ago, Seiford (2005) mentioned that he found at least 2800 published articles on DEA in various management and planning publications. Clearly, nowadays this number is already much higher. The DEA methodology has also expanded its scope towards other disciplines. Currently, in the city performance context, there are several assessment studies that have applied DEA models to measure economic efficiency among cities, which are regarded as so-called Decision-Making Units (DMUs) in the DEA jargon.

An interesting new endeavour was developed by Anderson and Petersen (1993) who developed the Super-Efficiency (SE hereafter) model based on the original CCR-I (input oriented) model (Charnes et al. 1978) so as to arrive at a complete ranking of all efficient DMUs (even though they have all initially an efficiency score equal to 1.0). The efficiency scores from an SE-model are then obtained by eliminating the data on the DMU to be evaluated from the solution set in order to examine its relative effect. These values are then used to rank the initial efficient DMUs, and consequently, efficient DMUs may then obtain an efficiency score above 1.0, while the scores of all inefficient DMUs remain identical and below 1.0. This SE-DEA model has coped with a major shortcoming in the use of the original DEA model, so that in our application, we will use the SE-DEA model.

A wealth of introductions into DEA and of applications to city efficiency rankings can be found in Borger et al. (1996), Worthington et al. (2000), Afonso et al. (2006), Suzuki et al. (2008), Nijkamp et al. (2009), Kourtit et al. (2013), Kourtit et al. (2017), Suzuki and Nijkamp (2016), Suzuki and Nijkamp (2017a), Suzuki et al. (2017b), and Suzuki and Nijkamp (2018). This large number of applied studies shows that an operational analysis of city efficiency in a competitive environment is an important, but also intriguing research topic in the urban and regional science literature. DEA has in the meantime demonstrated its great potential in providing a quantitative basis for comparative and benchmark studies in efficiency or productivity analysis.

It should be noted that DEA was originally developed to analyse the relative efficiency of a DMU by constructing a piecewise linear production frontier, and projecting the performance of each DMU onto that frontier. A DMU that is located on the frontier is efficient, whereas a DMU that is below the frontier is inefficient. The idea of DEA is that an inefficient DMU can become efficient by reducing its inputs, or by increasing its outputs. In the standard DEA approach, this is achieved by a uniform reduction in all inputs (or a uniform increase in all outputs). However, in principle, there are an infinite number of possible improvements that could be implemented in order to reach the efficiency frontier, and, hence, there are many solution trajectories, if a DMU wants to enhance its efficiency.

It is noteworthy that, in the past few decades, the existence of many possible efficiency improvement solutions has prompted a rich literature on the methodological integration of Multiple Objective Linear Programming (MOLP) and DEA models. Here, we provide a concise overview (see for more information Suzuki and Nijkamp 2017a). One of the first contributions was offered by Golany (1988), who proposed an interactive MOLP procedure, which aimed to generate a set of efficient points for a DMU. This model allows a decision maker to select the preferred set of output levels, given the prior input levels. Later on, Thanassoulis and Dyson (1992), Joro et al. (1998), Halme et al. (1999), Frei et al. (1999), Korhonen and Siljamäki (2002), Korhonen et al. (2003), Silva et al. (2003), Lins et al. (2004), Washio et al. (2012), and Yang and Morita (2013) also developed complementary efficiency improvement solutions. In particular, Suzuki et al. (2010) proposed a new projection model, called a Distance Friction Minimisation (DFM) model. In this approach, a generalised distance indicator is employed to assist a DMU so as to improve its efficiency by a movement towards the efficiency frontier surface. Of course, the direction of the efficiency improvement depends on the input/output data characteristics of the DMU. It is then plausible to approximate suitable projection functions for the minimisation of distance by using a Euclidean distance in weighted space. A convenient form of multidimensional projection functions that serves to improve efficiency is given by a Multiple Objective Quadratic Programming (MOQP) model, which aims to minimise the aggregated input reductions, as well as the aggregated output increases. Thus, the DFM approach can generate a new contribution to efficiency enhancement problems in decision analysis by employing a weighted Euclidean projection function, while, at the same time, it might address both an input reduction and output increase.

The DFM model is able to calculate either an optimal input reduction value or an optimal output increase value in order to reach an efficiency score of 1.0. Clearly, in reality this might be hard to reach for low-efficiency DMUs. Recently, Suzuki et al. (2015) developed an adjusted DEA model, which emerged from a blend of the DFM and the target-oriented (TO) approach based on a Super-Efficiency (SE) model, in order to generate an appropriate efficiency-improving projection model. The TO approach specifies a target-efficiency score (TES) for inefficient DMUs. This approach is able to compute both an input reduction value and an output increase value in order to achieve the pre-defined TES. However, this TO approach assumes that TES is set by a decision-maker or policy-maker, which may incorporate subjective elements. Based on this approach, Suzuki and Nijkamp (2019) developed an objective target setting model in the TO-DFM approach, namely the Autoconfiguration Target (AT) - DFM model. This approach can compute an input reduction value and an output increase value in order to achieve a TES in a more objective way. However, in many cases, the input and output factors may not be flexible or adjustable due to the indivisible nature or inertia in the input and output factors. For example, if road infrastructure is an input variable, it is evident that one cannot build half a road. Usually, the DEA model does not allow for a non-controllable or a fixed input factor. Therefore, it is desirable to integrate the AT-DFM model with a fixed factor (FF) model (see Suzuki et al. 2011) in order to cope with realistic circumstances in our search for a feasible efficiency improvement projection. This will be further pursued in the present paper.

Based on these backgrounds, the first aim of this paper is now to undertake a multi-faceted performance ranking of 12 large cities in the Asian region, especially focused on Chinese large cities (Hong Kong, Shanghai and Beijing) by means of a SE-DEA.

In this paper, we will use a data set on measurable indicators for the cities under consideration, viz. the Global Power City Index (GPCI), produced by the Institute for Urban Strategies and organized by the Mori Memorial Foundation in Tokyo. We will use here data for the year 2016, which offer a great potential for a comparative benchmark analysis for large Asian cities. We have selected as relevant DMUs the available set of 12 Asian cities from the GPCI system. For our comparative performance analysis of the cities under consideration, we consider as evaluation criteria: economic performance, technological innovativeness, interaction, and cultural resources. In this comparative analysis, we will conceive of 'cultural resource' as a production factor that cannot be flexibly adjusted. The second aim of this paper is to integrate the newly created AT-DFM model with a fixed factor (FF) so as to consider realistic circumstances and requirements in an operational strategy for a feasible efficiency improvement. The above-mentioned new AT-DFM-FF model will in the present study be applied in order to provide an efficiency-improving projection for inefficiency enhancement of several large Asian cities, with a special focus on Chinese cities.

The paper is organised as follows. Section 2 will summarise briefly our DFM methodology, while Section 3 proposes the newly developed model, which is a Fixed Factor (FF) model in the framework of the AT-DFM model. Next, Section 4 presents an application of performance assessment of 12 large Asian cities. Then, Section 5 offers the efficiency improvement projection results based on our new AT-DFM-FF model for inefficient cities. Finally, Section 6 draws some conclusions.

2. Outline of the Distance Friction Minimisation (DFM) Approach

We will first offer a brief description of the normal DFM approach. The standard Charnes et al. (1978) model (abbreviated hereafter as the CCR-I (input) model) for a given DMU$_j$ $(j = 1, \cdots, J)$ to be evaluated in any trial k (where k ranges over 1, 2 …, J) may be represented as the following fractional programming (FP_k) problem (see for full description Suzuki and Nijkamp 2017a):

$$
\begin{aligned}
(FP_k) \qquad & \max_{v,u} \quad \theta = \frac{\sum_s u_s y_{sk}}{\sum_m v_m x_{mk}} \\
\text{s.t.} \qquad & \frac{\sum_s u_s y_{sj}}{\sum_m v_m x_{mj}} \leq 1 \ \ (j = 1, \cdots, J) \qquad (1) \\
& v_m \geq 0, \ u_s \geq 0,
\end{aligned}
$$

where θ represents an objective variable function (efficiency score); x_{mj} is the volume of input m (m = 1,…, M) for DMU$_j$(j = 1,…,J); y_{sj} is the output s (s = 1,…,S) of DMU j; and v_m and u_s are the weights given to input m and output s, respectively. Model (1) is often called an input-oriented CCR model, while its reciprocal (i.e. an interchange of the numerator and denominator in the objective function (1) with a specification as a minimisation problem under an appropriate adjustment of the constraints) is usually known as an output-oriented CCR model. Model (1) is obviously a fractional programming model, which may be solved stepwise by first assigning an arbitrary value to the denominator in (1), and next maximising the numerator (see also Cooper et al. (2006) and Suzuki et al. (2010)).

The improvement projection $(\hat{x}_k, \hat{y}_k)$ can now be defined in (2) and (3) as:

$$\hat{x}_k = \theta^* x_k - s^{-*}; \qquad (2)$$
$$\hat{y}_k = y_k + s^{+*} \qquad (3)$$

]

These equations indicate that the efficiency of (x_k, y_k) for DMU$_k$ can be improved if the input values are reduced radially by the ratio θ^* and the input excesses s^{-*} are eliminated (see Figure 1). It should be noted that the original DEA models presented in the literature have focused on a uniform input reduction or on a uniform output increase in the efficiency-improvement projections, as shown in Figure 1 (θ^*=OC'/OC).

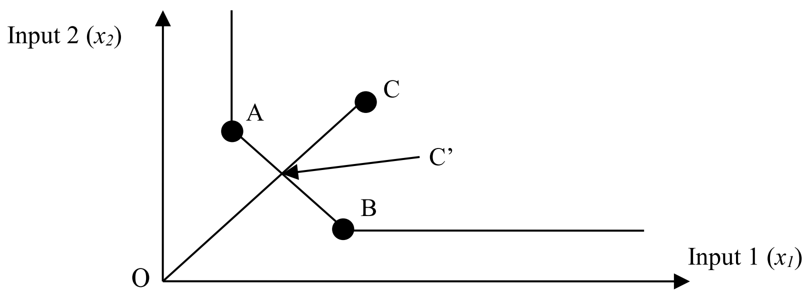


Figure 1 Illustration of original DEA projection in input space

The (v^*, u^*) values obtained as an optimal solution for formula (1) result in a set of optimal weights for DMU$_k$. Hence, (v^*, u^*) is the set of most favourable weights for DMU$_k$, measured on a ratio scale. Thus, v_m^* is the optimal weight for input item m, and its magnitude expresses how much in relative terms the item is contributing to efficiency. Similarly, u_s^* does the same for output item s. These values show not only which items contribute to the performance of DMU$_k$, but also the extent to which they do so. In other words, it is possible to express the distance frictions (or alternatively, the potential increases) in improvement projections.

We use next the optimal weights u_s^* and v_m^* from (1), and then describe the efficiency improvement projection model (see also Suzuki et al. (2010)). In this approach, a generalised distance indicator is employed to assist a DMU in improving its efficiency by a movement towards the efficiency frontier surface. Of course, the direction of the efficiency improvement depends on the input/output data characteristics of the DMU. It is now appropriate to define the projection functions for the minimisation of distance by using a Euclidean distance in weighted space. As mentioned earlier, a suitable form of multidimensional projection functions that serves to improve efficiency is given by a Multiple Objective Quadratic Programming (MOQP) model, which aims to minimise the aggregated input reductions, as well as the aggregated output increases. This DFM approach can generate a new contribution to efficiency enhancement problems in decision analysis by employing a weighted Euclidean projection function, and, at the same time, it might address both an input reduction and output increase. Here, we will only briefly sketch the various steps (for more details, we refer to Suzuki and Nijkamp 2017a).

First, the distance function Fr^x and Fr^y is specified by means of (4) and (5), which are defined by the Euclidean distance. Next, the following MOQP is solved by using d_{mk}^{x} (a reduction of distance for x_{mk}) and d_{sk}^{y} (an increase of distance for y_{sk}) as variables:

$$\min \ Fr^x = \sqrt{\textstyle\sum_m (v_m^* x_{mk} - v_m^* d_{mk}^x)^2} \tag{4}$$

$$\min \ Fr^y = \sqrt{\textstyle\sum_s \left(u_s^* y_{sk} - u_s^* d_{sk}^y\right)^2} \tag{5}$$

$$\text{s.t.} \quad \textstyle\sum_m v_m^* (x_{mk} - d_{mk}^x) = \frac{2\theta^*}{1+\theta^*} \tag{6}$$

$$\textstyle\sum_s u_s^* \left(y_{sk} + d_{sk}^y\right) = \frac{2\theta^*}{1+\theta^*} \tag{7}$$

$$x_{mk} - d_{mk}^x \geq 0 \tag{8}$$

$$d_{mk}^x \geq 0 \tag{9}$$

$$d_{sk}^y \geq 0, \tag{10}$$

where x_{mk} is the amount of input item m for any arbitrary inefficient DMU_k, while y_{sk} is the amount of output item s for any arbitrary inefficient DMU_k. The constraint functions (6) and (7) refer to the target values of input reduction and output augmentation. The proportional distribution of the input and output contributions in achieving efficiency is established as follows. The total efficiency gap to be covered by inputs and outputs is (1-θ*). The input and the output side contribute according to their initial levels 1 and θ*, implying shares θ*/(1+θ*) and 1/(1+θ*) in the improvement contribution. Clearly, the contributions from both sides equal (1-θ*) [θ*/(1+θ*)], and (1-θ*) [1/(1+θ*)]. Hence, we derive for the input reduction targets and the output augmentation targets the following expressions:

$$\text{input reduction target:} \textstyle\sum_m v_m^* (x_{mk} - d_{mk}^x) = 1 - (1-\theta^*) \times \frac{1}{(1+\theta^*)} = \frac{2\theta^*}{1+\theta^*}. \tag{11}$$

$$\text{output augmentation target: } \textstyle\sum_s u_s^* \left(y_{sk} + d_{sk}^y\right) = \theta^* + (1-\theta^*) \times \frac{\theta^*}{(1+\theta^*)} = \frac{2\theta^*}{1+\theta^*}. \tag{12}$$

An illustration of this approach is given in Figure 2.

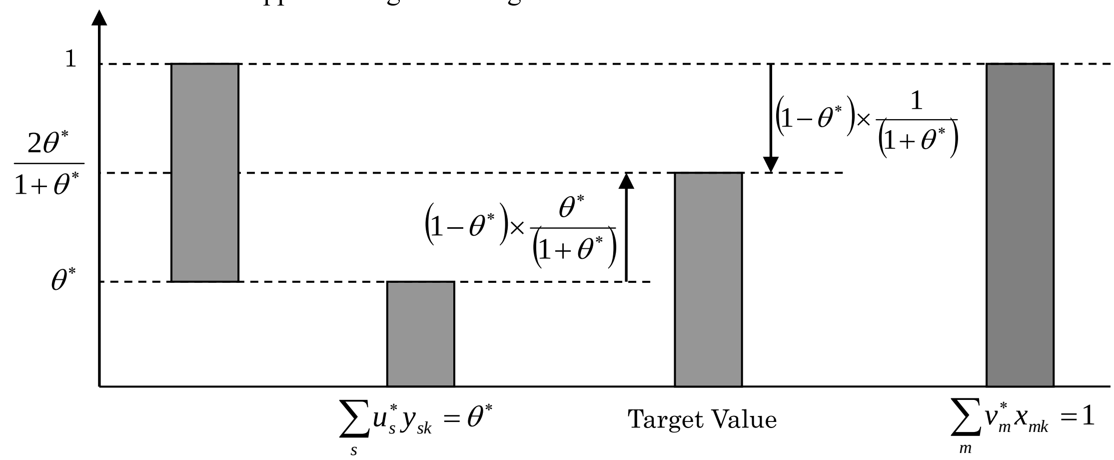


Figure 2 DFM model with an illustration of the relative contribution of inputs and outputs to closing the efficiency gap

It is now possible to determine each optimal distance d_{mk}^{x*} and d_{sk}^{y*} by using the MOQP model (4) - (10). The distance minimisation solution for an inefficient DMU_k can be expressed by means of formulas (13) and (14):

$$x_{mk}^* = x_{mk} - d_{mk}^{x*}; \tag{13}$$

$$y_{sk}^* = y_{sk} + d_{sk}^{y*}. \tag{14}$$

By means of the DFM model described above, it is possible to present a new efficiency-improvement solution based on the standard CCR projection. This means an increase in new promising options for efficiency-improvement strategies in DEA. The main advantage of the DFM model is that it yields an outcome on the efficient frontier that is as close as possible to the DMU's input and output profile (see Figure 3).

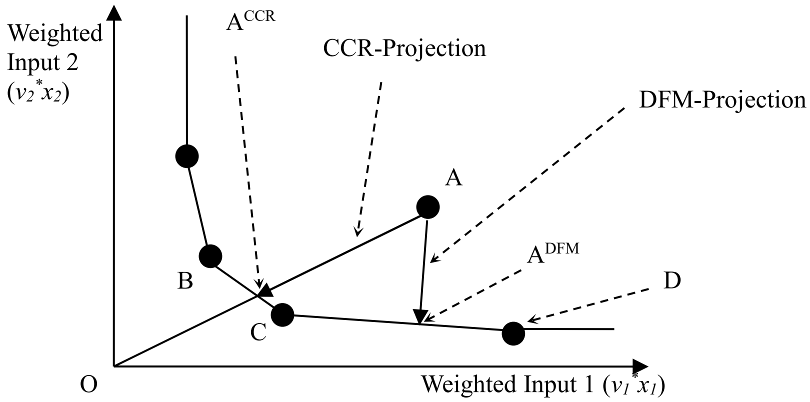


Figure 3 Degree of improvement of the DFM and the CCR projection in weighted input space

3.Design of an AT-DFM-FF Model

As mentioned above, the DFM model is able to calculate either an optimal input reduction value or an optimal output increase value in order to reach an efficiency score of 1.0. Clearly, in reality this might be hard to reach for low-efficiency DMUs. Recently, Suzuki et al. (2015) presented a newly developed adjusted DEA model, which emerged from a blend of the DFM and the target-oriented (TO) approach based on a Super-Efficiency (SE) model, in order to generate an appropriate efficiency-improving projection model. The TO approach specifies a target-efficiency score (TES) for inefficient DMUs. This approach is able to compute both an input reduction value and an output increase value in order to achieve the pre-defined TES. However, this TO approach assumes that TES is set by a decision or policy maker, which may introduce subjective elements. Based on this background, Suzuki and Nijkamp (2019) developed an objective target setting model in the TO-DFM approach, namely the Autoconfiguration Target (AT) - DFM model. This approach can compute an input reduction value and an output increase value in order to achieve a TES in objective way. However, in many cases, the input or output factor may not be flexible or adjustable due to the indivisible nature or inertia in the input or output factor. Usually, the DEA model does not allow for a non-controllable or a fixed (integer) factor. Therefore, it is desirable to integrate the AT-DFM model with a fixed factor (FF) model (see Suzuki et al. 2011) in order to cope with realistic circumstances in our search for a feasible efficiency improvement projection.

This paper proposes a new, so-called AT-DFM Fixed Factor (AT-DFM-FF hereafter) model, which incorporates the Autoconfiguration Target concept and Fixed Factor in a statistical way so as to set a TES. The AT-DFM-FF approach comprises the following steps:

Step 1. The Autoconfiguration Target Efficiency Score (ATES) with a Fixed Factor of case α for DMU_k (hereafter $ATES_k^{FF-\alpha}$) is set by the following specific statistical method. We compute here an average efficiency score for all DMU set μ, and a standard deviation of an efficiency score for all DMU set σ.

The SE-DEA model usually computes an efficiency score above 1.0 for efficient DMUs, although the original CCR model usually compute an efficiency score just equal 1.0 for efficient DMUs. This means that μ and σ depend on the specification of the model. Based on these observations, the present paper taken for granted that all efficiency scores for all efficient DMUs just hold at the value of 1.0. This helps maintain an objective setting for ATES.

Based on these statistical values, the $ATES^{FF}$ values for DMU_k are set as follows:

- Case 1: $0 < \theta^* < \mu - 2\sigma$, then $ATES_k^{FF-1} = \mu - 2\sigma$ (if $\mu - 2\sigma < 0$, then this case is eliminated)
- Case 2: $\mu - 2\sigma < \theta^* < \mu - \sigma$, then $ATES_k^{FF-2} = \mu - \sigma$ (if $\mu - 2\sigma < 0$, then we put it 0)
- Case 3: $\mu - \sigma < \theta^* < \mu$, then $ATES_k^{FF-3} = \mu$ (if $\mu - \sigma < 0$, then we put it 0)
- Case 4: $\mu < \theta^* < \mu + \sigma$, then $ATES_k^{FF-4} = \mu + \sigma$ (if $\mu + \sigma > 1$, then we put it 1)
- Case 5: $\mu + \sigma < \theta^* < \mu + 2\sigma$, then $ATES_k^{FF-5} = \mu + 2\sigma$ (if $\mu + 2\sigma > 1$, then we put it 1)
- Case 6: $\mu + 2\sigma < \theta^* < 1$, then $ATES_k^{FF-6}=1$(this is just same as a normal DFM model).

An illustration of this $ATES^{FF}$ concept is given in Figure 4.

Step 2. Solve $ATES_k^{FF-\alpha} = \frac{\theta^* + \frac{MP_k^{FF-\alpha}(1-\theta^*)(\theta^* - \sum_{s \in ND} u_s^* y_{sk})}{(1-\sum_{m \in ND} v_m^* x_{mk}) + (\theta^* - \sum_{s \in ND} u_s^* y_{sk})}}{1 - \frac{MP_k^{FF-\alpha}(1-\theta^*)(1-\sum_{m \in ND} v_m^* x_{mk})}{(1-\sum_{m \in ND} v_m^* x_{mk}) + (\theta^* - \sum_{s \in ND} u_s^* y_{sk})}}$. (15)

Then we get $MP_k^{FF-\alpha}$, which is a Magnification Parameter of $ATES_k^{FF-\alpha}$. The parameter $MP_k^{FF-\alpha}$ assumes an intermediate role by adjusting the input reduction target and the output increase target in formulas (19) and (20) in order to ensure an alignment of the $ATES_k^{FF-\alpha}$ and DFM projection score for DMU_k.

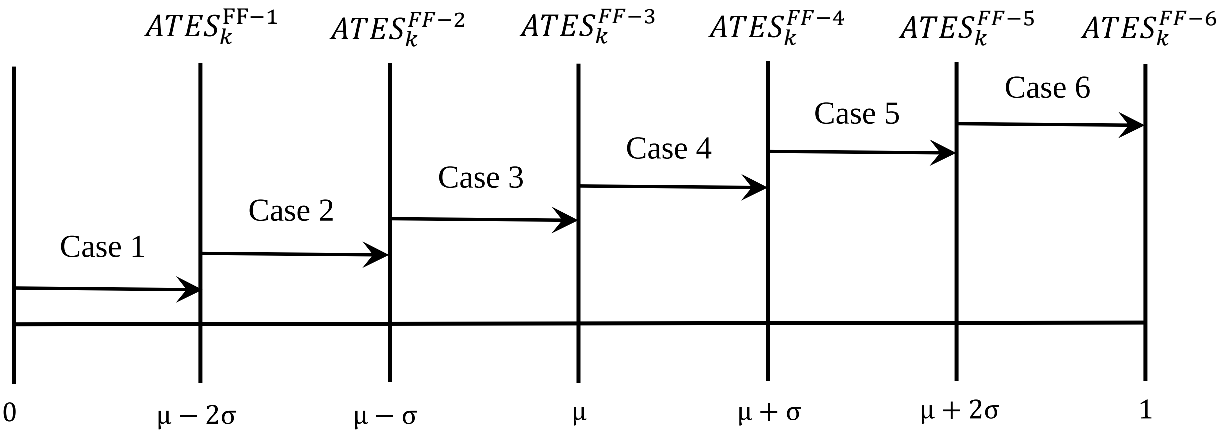


Figure 4 An illustration of the concept of $ATES^{FF}$

Step 3. Solve the AT-DFM-FF model by using formulas (16) – (23). Then, an optimal input reduction value and output increase value to reach a $ATES_k^{\alpha}$ can be calculated as follows:

$$\min \ Fr^x = \sqrt{\sum_{m \in D} (v_m^* x_{mk} - v_m^* d_{mk}^x)^2}; \tag{16}$$

$$\min \ Fr^y = \sqrt{\sum_{s \in D} \left(u_s^* y_{sk} - u_s^* d_{sk}^y\right)^2}; \tag{17}$$

$$\text{s.t.} \quad ATES_k^{FF-\alpha} = \frac{\sum_{s \in D} u_s^* (y_{sk} + d_{sk}^y) + \sum_{s \in ND} u_s^* y_{sk}}{\sum_{m \in D} v_m^* (x_{mk} - d_{mk}^x) + \sum_{m \in ND} v_m^* x_{mk}}; \tag{18}$$

$$\sum_{m \in D} v_m^* (x_{mk} - d_{mk}^x) + \sum_{m \in ND} v_m^* x_{mk} = 1 - \frac{MP_k^{FF-\alpha}(1-\theta^*)(1-\sum_{m \in ND} v_m^* x_{mk})}{(1-\sum_{m \in ND} v_m^* x_{mk}) + (\theta^* - \sum_{s \in ND} u_s^* y_{sk})}; \tag{19}$$

$$\sum_{s \in D} u_s^* \left(y_{sk} + d_{sk}^y\right) + \sum_{s \in ND} u_s^* y_{sk} = \theta^* + \frac{MP_k^{FF-\alpha}(1-\theta^*)(\theta^* - \sum_{s \in ND} u_s^* y_{sk})}{(1-\sum_{m \in ND} v_m^* x_{mk}) + (\theta^* - \sum_{s \in ND} u_s^* y_{sk})}; \tag{20}$$

$$x_{mk} - d_{mk}^x > 0; \tag{21}$$

$$d_{mk}^x \geq 0; \tag{22}$$

$$d_{sk}^y \geq 0, \tag{23}$$

where the symbols $m \in D$ and $s \in D$ refer to the set of 'discretionary' inputs and outputs, and the symbols $m \in ND$ and $s \in ND$refer to the set of 'non-discretionary' inputs and outputs.

The meaning of functions (16) and (17) is to consider only the distance friction of discretionary inputs and outputs. The constraint functions (19) and (20) are incorporated in the non-discretionary factors for the efficiency gap. The target values for input reduction and output augmentation with a balanced allocation depend on all total input-output scores and fixed factor situations, as presented in Figure 5 in the case of $ATES_k^{FF-\alpha} = 1.000$ (i.e. $MP_k^{FF-\alpha} = 1.000$). The calculated result of (19) will then coincide with the calculated result of (20).

Finally, the optimal solution for an inefficient DMU_k can now be expressed by means of (24) - (27):

$$x_{mk}^{**} = x_{mk} - d_{mk}^{x*} - s^{-**}, \ m \in D; \tag{24}$$

$$y_{sk}^{**} = y_{sk} + d_{sk}^{y*} + s^{+**}, \ s \in D; \tag{25}$$

$$x_{mk}^{**} = x_{mk}, \ m \in ND; \tag{26}$$

$$y_{sk}^{**} = y_{sk}, \ s \in ND. \tag{27}$$

The slacks s^{-**}, $m \in ND$ and s^{+**}, $s \in ND$ are not incorporated in (26) and (27), because these factors are 'fixed ' or 'non-discretionary' inputs and outputs, in a way similar to the Banker and Morey (1986) model. This approach will hereafter be described as the AT-DFM-FF approach.

An illustration of the AT-DFM-FF model is given in Figure 6.

From Figure 6, we also note that the AT-DFM-FF projection does not reach the efficiency frontier; thus, it may be one of the improvement goal projections to reach ATES^{FF} lower than 1.0.

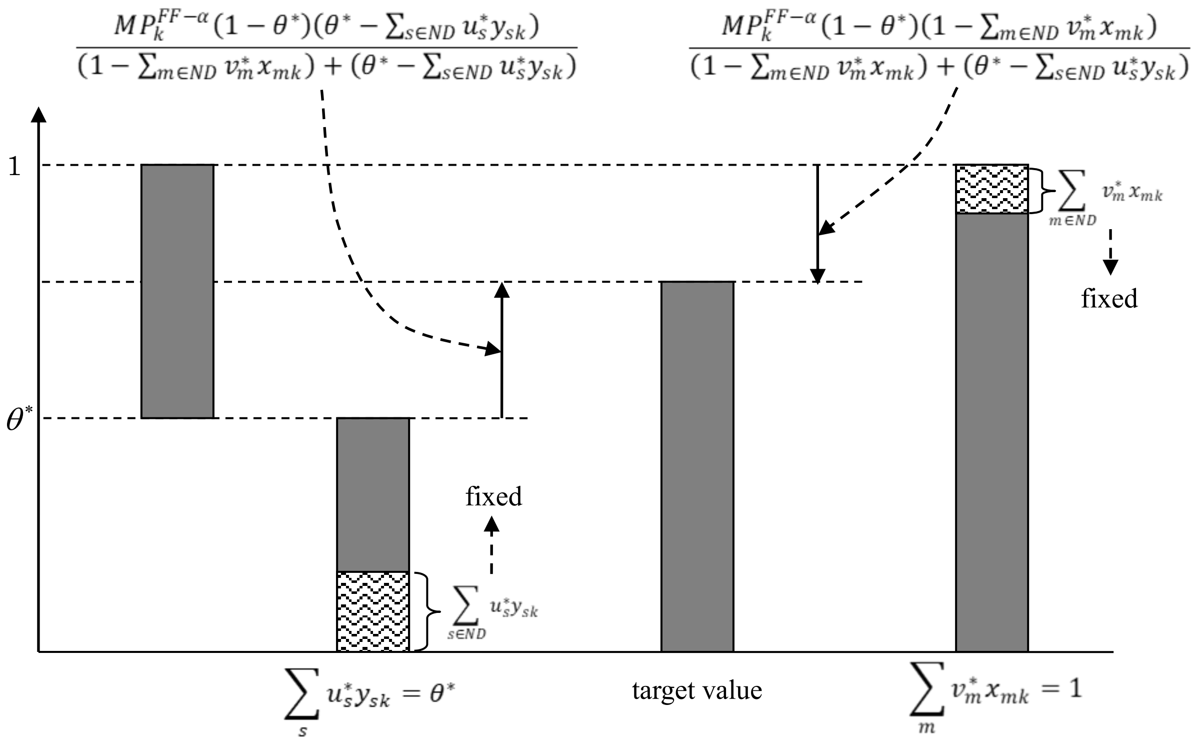


Figure 5 Distribution of the total efficiency gap (in the case of $ATES_k^{FF-\alpha} = 1.000$ ($MP_k^{FF-\alpha} = 1.000$))

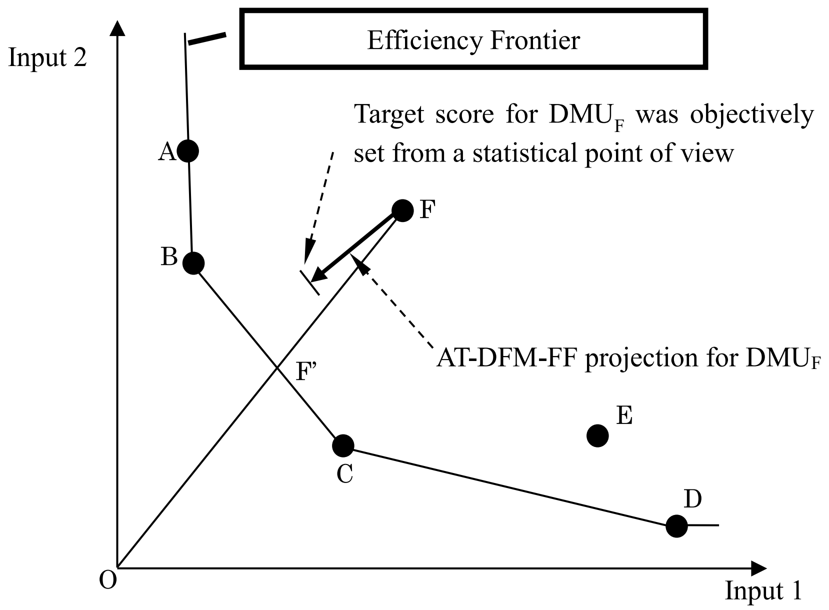


Figure 6 Illustration of the AT-DFM-FF model in input space

4. Performance Assessment of Asian Super-Cities

4.1 Database and analytical framework

For a systematic operational comparison of the Asian cities' performance outcomes, our empirical approach uses a unique and extensive data set on measurable indicators for the cities under consideration, viz. the Global Power City Index (GPCI), produced by the Institute for Urban Strategies and organized by the Mori Memorial Foundation in Tokyo. We will use here data for the year 2016, which offer a great potential for a comparative benchmark analysis for the Asian super cities. The GPCI database will thus be used here as a strategic tool to evaluate and to rank the comprehensive strategic power determinants of 12 large cities in this region, in terms of their strengths and their weaknesses.

The GPCI data base is a multi-annual world-wide data system on large cities, in which the comprehensive performance scores and rankings of these global cities are based on six main assessment categories, namely: Economy, Research & Development, Cultural Interaction, Livability, Environment, and Accessibility. Each of these main indicators classes is subdivided into a set of appropriate and measurable sub-indicators, so that finally a strictly consistent and carefully tested database on approx. 70 sub-indicators related to many world cities (40 in total) is created. The 70 indicators break down into 59 indicators based on statistics or numerical data, and 11 indicators using original questionnaires, some of which combine the scores from the questionnaires with additional numerical data. Thus the composition of data is as follows:

(1) Statistical sources (59 indicators)

- Whenever possible, official statistics are used as main sources of data.
- Quantitative data not derived from official statistics are taken from reliable sources such as academic research papers or other forms of publications which are clearly sourced.

(2) Original questionnaires (11 indicators)

- Questionnaires on residents and workers aimed at those living and/ or working in a target city.
- Questionnaires of experts aimed at those with experience living in and /or visiting multiple target cities.

This database is published annually since 2009. The 12 Asian cities used in our analysis are taken from this database. All further details are available in the above mentioned GPCI report.

In this paper we refer now to the "score by indicator" datasets in the GPCI report. Most of these indicator data are converted into a standardized indicator value, falling in between 100 and 0, so that the data can be evaluated according to a uniform standard measurement. The highest performance of an indicator receives a score equal to 100, and the poorest a score of 0.

The DMUs (decision-making units or cities) used in our comprehensive analysis are listed in Table 1.

Table 1 A list of Asian super cities

Bangkok	Osaka
Beijing	Seoul
Fukuoka	Shanghai
Hong Kong	Singapore
Kuala Lumpur	Taipei
Mumbai	Tokyo

For our comparative performance analysis of the cities under consideration, we consider as evaluation criteria: economic performance, technological innovativeness, cultural resource and interaction. Based on this viewpoint, we will select and introduce now 3 relevant input and 2 relevant output items as follows:

Input (I):

- (I1) Number of Employees
- (I2) Research and Development Expenditures
- (I3) Cultural Resources (The value of this indicator was calculated by adding up the 'Environment of Creative Activities' and 'Opportunities of Cultural, Historical and Traditional Interaction')

Output (O):

- (O1) Nominal GDP
- (O2) Volume of Interaction (The score of this indicator was calculated by adding up the indicator scores 'Number of Visitors from Abroad' and 'Number of International Students')

Based on this background information, this paper will analyze the performance of Asian large cities based on 3 input and 2 outputs, as shown in Figure 7.

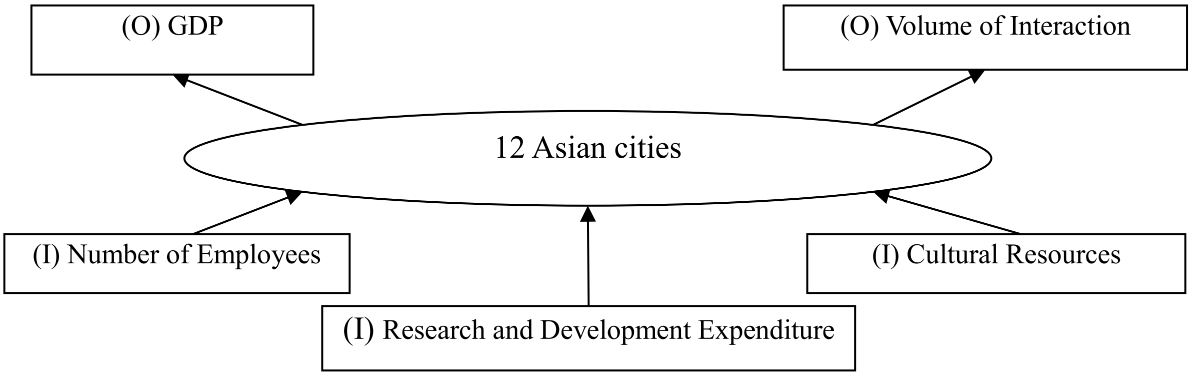


Figure 7 Input and Output items

4.2 Efficiency evaluation based on the Super-Efficiency CCR-I model

The performance assessment results for the 12 Asian large cities based on the SE-CCR-I model are presented in Figure 8.

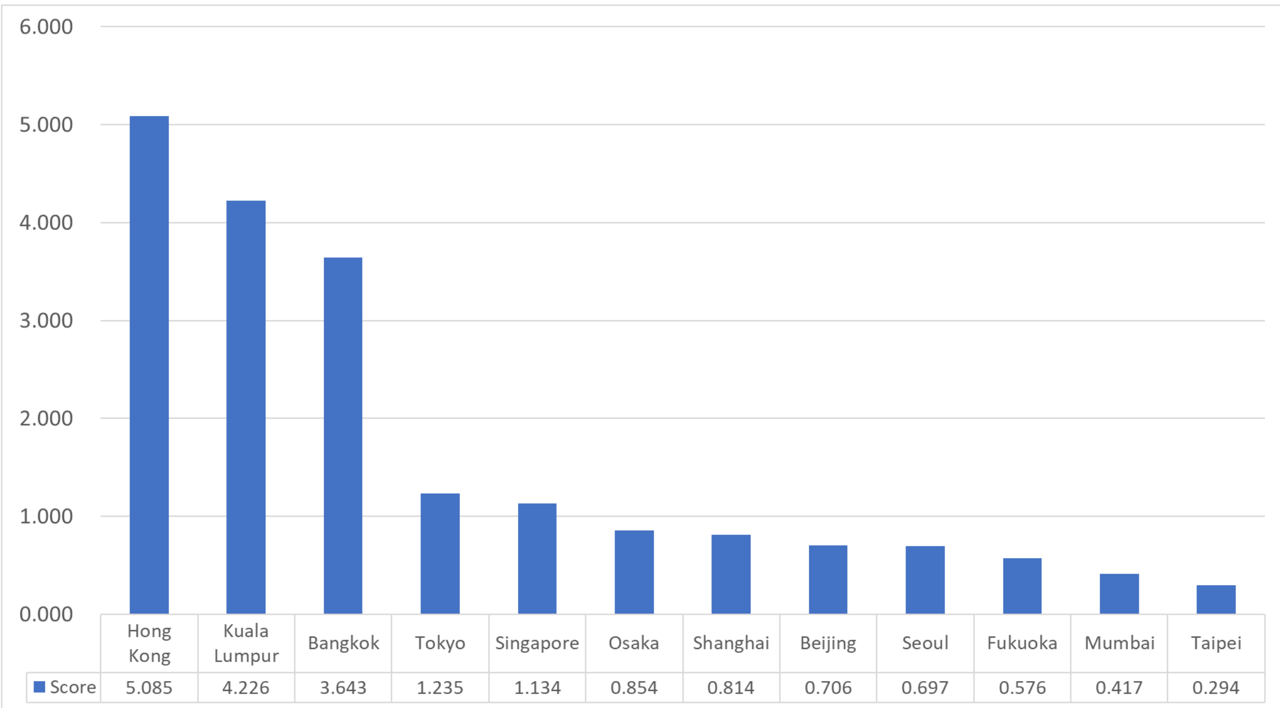


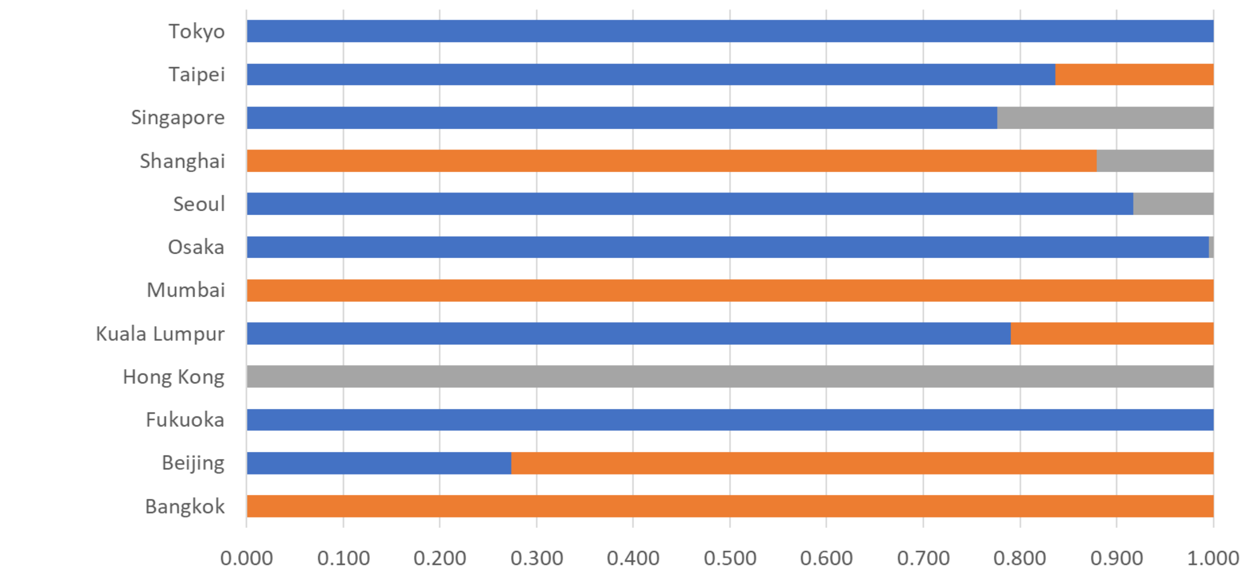
Figure 8 Efficiency scores for Asian large cities based on the SE-DEA model

From this figure, it can be seen that Hong Kong, Kuala Lumpur, Bangkok, Tokyo and Singapore may be regarded as super-efficient cities in the Asian context. It also appears that Osaka, Shanghai, Beijing, Seoul, Fukuoka, Mumbai and Taipei are evaluated to be inefficient cities.

We will now especially focus on Chinese cites. It can be seen that Hong Kong is a top performing city in the Asian region. On the other hand, Shanghai and Beijing are evaluated to be inefficient cities. Thus, these inefficient Chinese cities may need an efficiency enhancement strategy.

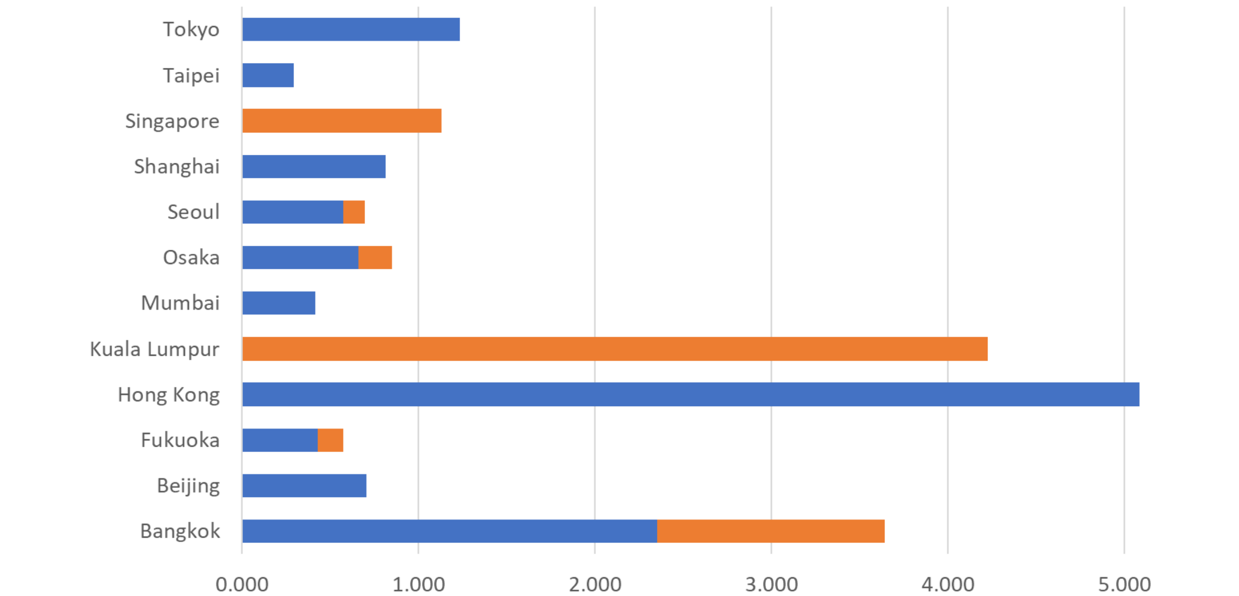
4.3 Optimum weights for input and output items

As mentioned in the above section, Chinese cities may have similar characteristics. We will especially focus on the Chinese context here, and we will analyze and consider this from the viewpoint of optimum weights for input and output items. The optimum weight is the set of most favorable weights for each DMU, so that we can find the relative importance of each indicator with reference to the value of each input and output items for each DMU. These values show not only which items contribute to the performance of a DMU, but also to what extent they do so. The optimum weights for input and output items for each city are presented in Figure 9 and 10.



	Bangkok	Beijing	Fukuoka	Hong Kong	Kuala Lumpur	Mumbai	Osaka	Seoul	Shanghai	Singapore	Taipei	Tokyo
VX(1) Number of Employees	0.000	0.274	1.000	0.000	0.790	0.000	0.995	0.917	0.000	0.777	0.837	1.000
VX(2) R&D Expenditure	1.000	0.726	0.000	0.000	0.210	1.000	0.000	0.000	0.879	0.000	0.163	0.000
VX(3) Cultural Resources	0.000	0.000	0.000	1.000	0.000	0.000	0.005	0.083	0.121	0.223	0.000	0.000

Figure 9 Optimum weights for input items



	Bangkok	Beijing	Fukuoka	Hong Kong	Kuala Lumpur	Mumbai	Osaka	Seoul	Shanghai	Singapore	Taipei	Tokyo
UY(1) Nominal GDP	2.352	0.706	0.433	5.085	0.000	0.417	0.659	0.577	0.814	0.000	0.294	1.235
UY(2) Volume of Interaction	1.290	0.000	0.143	0.000	4.226	0.000	0.194	0.120	0.000	1.134	0.000	0.000

Figure 10 Optimum weights for output items

From Figure 9 and 10, it can be seen that, for instance, Hong Kong obtains a weight for Cultural Resources equal to 1.000 in its inputs, while it obtains for GDP a weight of 5.085 in its output. It can also be seen that Shanghai obtains a weight for R&D equal to 0.879 and for Cultural Resource equal to 0.121 in its inputs, while it obtains for GDP a weight of 0.814 in its output, while Beijing obtains a weight for Number of Employees equal to 0.274 and for R&D equal to 0.726 in its inputs, while it obtains for GDP a weight of 0.706 in its output.
From these findings, we notice that Chinese cities reveal features similar to optimum weights, especially since these cities have a commonality feature that have a high value for R&D in input items and for GDP in output items. Based on this fact, Chinese cities, especially Hong Kong have a feature that has an advantage for GDP as an output item compared to other cities.

5. Efficiency improvement projection based on the SE-CCR-I, DFM and AT-DFM-FF models

Next, the above-mentioned AT-DFM-FF model is used to analyse realistic circumstances and to determine the requirements for an operational strategy for a feasible efficiency improvement in inefficient cities in Asia. In this comparative analysis, we will conceive of 'cultural resource' as a production factor that cannot be flexibly adjusted.

In generally, the TES (Target Efficiency Score) may be set by a policy- or decision-maker based on public promises or the actual situation. Our DFM model maintains flexibility of the value setting by such changing situations. However, if the TES may require a value setting in a less arbitrary way, our new AT-DFM-FF model is more appropriate. Based on the AT-DFM-FF model as a new foundation, we computed the $ATES^{FF}$ values as shown in Table 2 and Figure 11.

Table 2 List of statistical values

Items	Denotation	Score
Average	μ	0.780
Standard deviation	σ	0.071
$ATES_k^{FF-1}$	μ-2σ	0.637
$ATES_k^{FF-2}$	μ-σ	0.708
$ATES_k^{FF-3}$	μ	0.780
$ATES_k^{FF-4}$	μ＋σ	0.851
$ATES_k^{FF-5}$	μ＋2σ	0.922

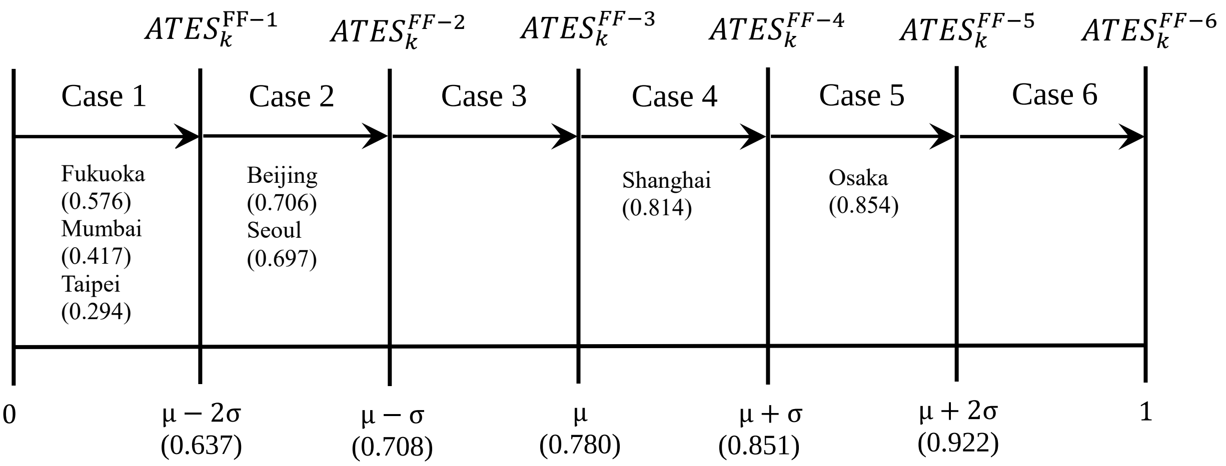
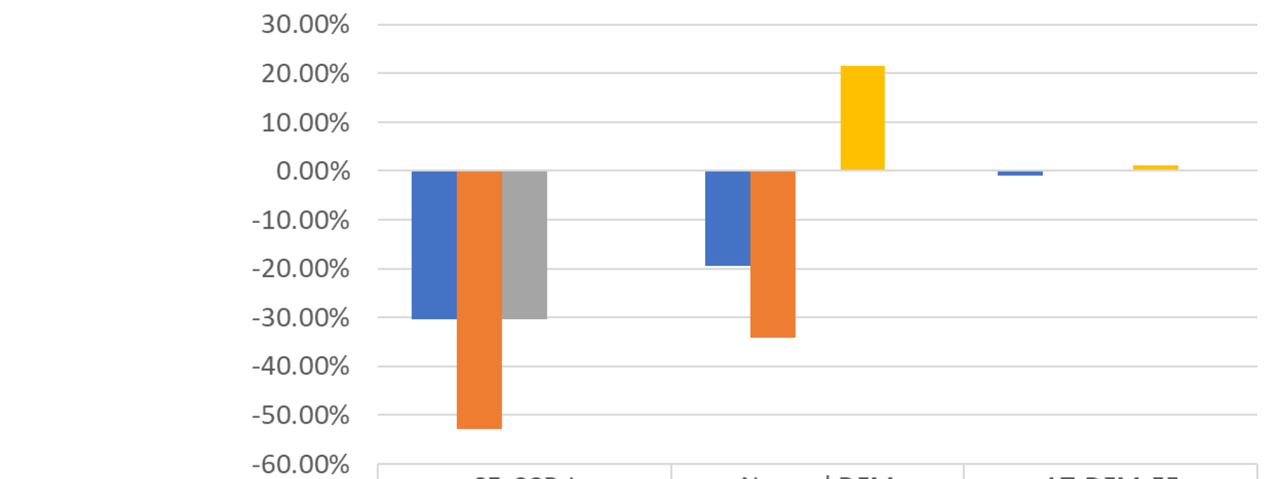


Figure 11 An illustration of $ATES^{FF}$ and position for each DMU

We will use here Seoul as an illustrative Case 2 and point of reference, and present an efficiency improvement projection result. The efficiency score appears to be 0.697 (see Figure 11). We assume now that the $ATES^{FF\text{-}2}$ value is automatically set for Case 2 at 0.708 ($ATES_k^{FF-2}$). The resulting input reduction values and the output increase values based on the SE-CCR-I, the standard DFM and the AT-DFM-FF model are presented in Figure 12.

From Figure 12, it appears that the standard DFM model shows clearly that a different – and likely more efficient – solution than the SE-CCR-I projection is available for reaching the efficiency frontier. For instance, the SE-CCR-I projection shows that a reduction in Number of Employees by 30.34%, in R&D Expenditure by 52.91% and in Cultural Resources by 30.34% are required to become efficient. On the other hand, the standard DFM results show that a reduction in Number of Employees by 19.50% and R&D Expenditure by 34.08%, together with an increase in the Nominal GDP of 21.60%, is needed to become efficient.

The AT-DFM-FF model is clearly able to provide a more realistic efficiency-improvement plan, as compared to the results of the SE-CCR-I and the standard DFM model. For instance, the AT-DFM-FF results show that a reduction in Number of Employees of 0.88 %, and an increase in Nominal GDP of 1.06 % are required to reach the $ATES_k^{FF-2}$ level of 0.708.



	SE-CCR-I	Normal DFM	AT-DFM-FF
(I)Number of Employees	-30.34%	-19.50%	-0.88%
(I)R&D Expenditure	-52.91%	-34.08%	0.00%
(I)Cultural Resources	-30.34%	0.00%	0.00%
(O)Nominal GDP	0.00%	21.60%	1.06%
(O)Volume of Interaction	0.00%	0.00%	0.00%

Figure 12 Efficiency-improvement projection results based on the SE-CCR-I, standard DFM and AT-DFM-FF model (Seoul)

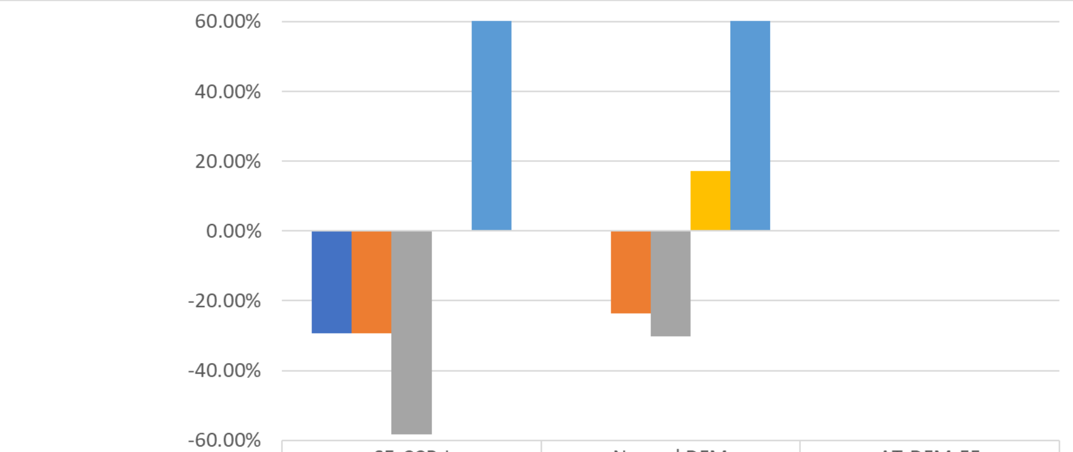
The results of an efficiency improvement projection based on the application of our SE-CCR-I model and the AT-DFM models for Chinese cities will now be presented Figure 13 and 14.

Regarding Beijing, the efficiency score appears to be 0.706 (see Figure 11). We assume now that the $ATES^{FF\text{-}2}$ value is endogenously set for Case 2 at 0.708 ($ATES_k^{FF-2}$). From Figure 11 we can now infer that, if Beijing implements an efficiency improvement plan based on the SE-CCR-I model, a reduction in Number of Employees by 29.38%, the R&D Expenditure by 29.38% and the Cultural Resources by 58.34%, together with an increase in the Volume of Interaction of 221.31%, is needed to become efficient. Furthermore, the standard DFM results in Figure 11 show that Beijing should reduce its R&D Expenditure by 23.72% and the Cultural Resources by 30.25%, together with an increase in the Nominal GDP of 17.22% and the Volume of Interaction of 335.89%, in order to become efficient. On the other hand, the AT-DFM-FF results in Figure 11 show that a reduction in R&D Expenditure of 0.22%, and an increase in Nominal GDP of 0.16% would be needed. From the above finding, we note that the AT-DFM-FF model is able to provide a more realistic efficiency-improvement plan, compared to the SE-CCR-I and the standard DFM. Note also that also here Cultural Resources is interpreted in the application as a fixed factor in the AT-DFM-FF model.

Regarding Shanghai, the efficiency score appears to be 0.814 (see Figure 11). We assume here that the $ATES^{FF\text{-}4}$ value is set for Case 4 at 0.851 ($ATES_k^{FF-4}$). From Figure 12 we can derive that, if Shanghai implements an efficiency improvement plan based on SE-CCR-I model, a reduction in Number of Employees by 41.65%, the R&D

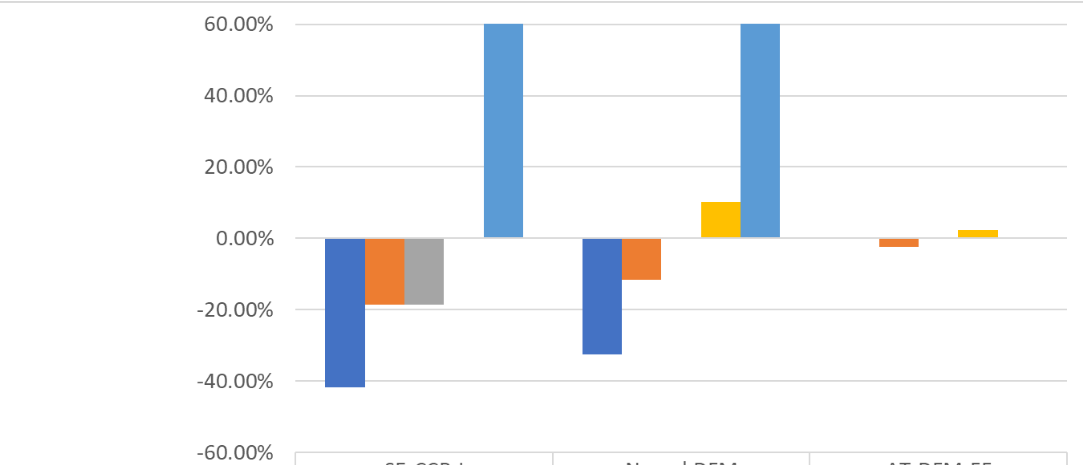
Expenditure by 18.65% and the Cultural Resources by 18.65%, together with an increase in the Volume of Interaction of 198.30%, is required to become efficient. Furthermore, the normal DFM results in Figure 12 show that Shanghai should reduce should reduce its Number of Employees by 32.59%, the R&D Expenditure by 11.66% and the Cultural Resources by 0.21%, together with an increase in Nominal GDP of 10.28% and in Volume of Interaction of 240.47%, in order to become efficient. On the other hand, the AT-DFM-FF results in Figure 12 show that a reduction in R&D Expenditure of 2.40%, and an increase in Nominal GDP of 2.40% would be needed. From the above finding, we also note that the AT-DFM-FF model is able to offer a more realistic efficiency-improvement plan, compared to the SE-CCR-I and standard DFM. It is noteworthy that also here Cultural Resources is interpreted in our illustrative application as a fixed factor in the AT-DFM-FF model.

From these facts, we may draw the conclusion that the AT-DFM-FF model is able to produce a reasonable realistic efficiency improvement projection than the previous SE-CCR-I and standard DFM models.



	SE-CCR-I	Normal DFM	AT-DFM-FF
(I)Number of Employees	-29.38%	0.00%	0.00%
(I)R&D Expenditure	-29.38%	-23.72%	-0.22%
(I)Cultural Resources	-58.34%	-30.25%	0.00%
(O)Nominal GDP	0.00%	17.22%	0.16%
(O)Volume of Interaction	221.31%	335.89%	0.00%

Figure 13 Efficiency-improvement projection results based on the SE-CCR-I, standard DFM and AT-DFM-FF model (Beijing)



	SE-CCR-I	Nomal DFM	AT-DFM-FF
(I)Number of Employees	-41.65%	-32.59%	0.00%
(I)R&D Expenditure	-18.65%	-11.66%	-2.40%
(I)Cultural Resources	-18.65%	-0.21%	0.00%
(O)Nominal GDP	0.00%	10.28%	2.40%
(O)Volume of Interaction	198.30%	240.47%	0.00%

Figure 14 Efficiency-improvement projection results based on the SE-CCR-I, standard DFM and AT-DFM-FF model (Shanghai)

The aggregate results of an efficiency improvement projection based on the application of SE-CCR-I, standard DFM and AT-DFM-FF models for other inefficient Asian cities are presented in Table 3 (θ** in Table 3 expresses the efficiency score after the improvement projection).

Table 3 Efficiency-improvement projection results of the SE-CCR and AT-DFM model

		SE-CCR-I		Nomal DFM		AT-DFM-FF	
DMU	Score	Score(θ**)		Score(θ**)		Score(θ**)	
I/O	Data	Difference	%	Difference	%	Difference	%
Fukuoka	0.576	1.000		1.000		0.637	
(I)Number of Employees	5.4	-2.290	-42.40%	-1.453	-26.90%	-0.272	-5.04%
(I)R&D Expenditure	8.5	-5.114	-60.16%	-3.829	-45.04%	0.000	0.00%
(I)Cultural Resources	6.2	-2.722	-43.90%	-2.725	-43.96%	0.000	0.00%
(O)Nominal GDP	4.6	0.000	0.00%	1.647	35.81%	0.308	6.70%
(O)Volume of Interaction	10.1	0.000	0.00%	0.000	0.00%	0.000	0.00%
Mumbai	0.417	1.000		1.000		0.637	
(I)Number of Employees	35.9	-23.333	-65.00%	-18.159	-50.58%	0.000	0.00%
(I)R&D Expenditure	0.4	-0.233	-58.33%	-0.165	-41.18%	-0.084	-20.92%
(I)Cultural Resources	28	-19.133	-68.33%	-15.482	-55.29%	0.000	0.00%
(O)Nominal GDP	3.4	0.000	0.00%	1.400	41.18%	0.711	20.92%
(O)Volume of Interaction	0.9	23.533	2614.81%	33.594	3732.68%	0.000	0.00%
Osaka	0.854	1.000		1.000		0.922	
(I)Number of Employees	16.1	-2.355	-14.63%	-1.277	-7.93%	-0.623	-3.87%
(I)R&D Expenditure	22.1	-6.753	-30.56%	-4.856	-21.97%	0.000	0.00%
(I)Cultural Resources	14.9	-2.179	-14.63%	-1.107	-7.43%	0.000	0.00%
(O)Nominal GDP	21	0.000	0.00%	2.145	10.22%	1.052	5.01%
(O)Volume of Interaction	40.1	0.000	0.00%	0.000	0.00%	0.000	0.00%
Seoul	0.697	1.000		1.000		0.708	
(I)Number of Employees	36.7	-11.136	-30.34%	-7.157	-19.50%	-0.323	-0.88%
(I)R&D Expenditure	38	-20.105	-52.91%	-12.951	-34.08%	0.000	0.00%
(I)Cultural Resources	10.9	-3.307	-30.34%	0.000	0.00%	0.000	0.00%
(O)Nominal GDP	36.8	0.000	0.00%	7.948	21.60%	0.391	1.06%
(O)Volume of Interaction	76.8	0.000	0.00%	0.000	0.00%	0.000	0.00%
Taipei	0.294	1.000		1.000		0.637	
(I)Number of Employees	8.5	-6.003	-70.63%	-5.547	-65.26%	-3.748	-44.10%
(I)R&D Expenditure	6.3	-4.450	-70.63%	-2.868	-45.52%	0.000	0.00%
(I)Cultural Resources	7.5	-6.714	-89.52%	-6.702	-89.36%	0.000	0.00%
(O)Nominal GDP	3.8	0.000	0.00%	2.075	54.59%	1.402	36.89%
(O)Volume of Interaction	4.2	1.445	34.40%	1.704	40.57%	0.000	0.00%

6. Conclusion

In this paper, we have designed an empirical assessment framework and presented findings on the efficiency of large Asian cities. From these results, it is clear that Hong Kong, Kuala Lumpur, Bangkok, Tokyo and Singapore may be regarded as super-efficient cities in the Asian context. It also appears that Osaka, Shanghai, Beijing, Seoul, Fukuoka, Mumbai and Taipei are evaluated here as inefficient cities. It is also clear that Hong Kong is a prime super city in the Asian region.

We have presented in our study also a new DEA methodology, the AT-DFM-FF model. Its feasibility for improving the efficiency of Asian large cities was tested. From the above findings, we note that the AT-DFM-FF model is able to present a realistic efficiency-improvement programme which incorporates a more objective way to set a target efficiency score including fixed factor. Our AT-DFM model is able to programme a realistic efficiency-improvement city development plan, and may thus provide a meaningful contribution to planning for efficiency improvement of large cities in Asia, but also for other cities in mature or emerging economies.

The present study has clearly demonstrated the great potential of DEA for comparative and decision-making purposes. In particular, the new DEA variants proposed and tested in this paper have clearly proven the power of advanced DEA methods. It is also evident that the DEA methodology offers a new and innovative spectrum for further evidence-based comparative studies.

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