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Article

Winners in the urban champions league: A performance assessment of Japanese cities by means of dynamic and super-efficient DEA

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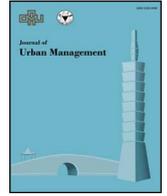
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Research Article

Winners in the urban champions league – A performance assessment of Japanese cities by means of dynamic and super-efficient DEA[☆]

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ABSTRACT

This paper aims to provide an advanced dynamic efficiency assessment methodology for city performance strategies in Japan, based on an extended and super-efficient Data Envelopment Analysis (DEA). The use of this novel efficiency-improving approach originates from earlier research based on the so-called Distance Friction Minimisation (DFM) method. In the present study we develop a new multi-period model from a blend of a Target-Oriented (TO) DFM model including a dynamic approach. This new model is able to present a more realistic efficiency improvement projection comprising a dynamic system of target-settings to achieve a target improvement level so as to programme more realistic policy actions. The above-mentioned Dynamic TO-DFM model will be applied to and tested for a multi-dimensional efficiency assessment of several large Japanese cities. In this study, we consider due to comparative data limitations, two inputs (population and city budget) and two outputs (GDP and tax revenues). Based on these items, this study assesses the relative economic performance of 16 Japanese big cities by means of the above described, extended super-efficient DEA model. Finally, we present an efficiency improvement programme based on the Dynamic TO-DFM model for enhancing the position of inefficient cities.

1. Introduction

Japan -like many other Asian countries- shows a high degree of spatial and demographic dynamics. Compared to other nations in Asia, the Japanese economy is characterized by quite some turbulence in the past decades. We will briefly illustrate the dynamics in the Asian countries based on population changes as presented in Fig. 1. We have chosen this demographic information, as this is a relatively easy variable to predict over a relatively long time period.

From Fig. 1, it can easily be seen that Japan is already in a transition process towards a depopulating society as a result of the structural ageing process. Korea, Thailand and China will also become depopulating nations in the period 2020 to 2040, while other countries will sooner or later also show a downward trend in the rate of population growth (for more detail, see Suzuki and Nijkamp (2017b)). It should be added that the spatial distribution of people – despite declining growth rates of the population- is not showing a stable pattern over the past decades. On the contrary, we observe that an increasing share of people lives in urban areas (the so-

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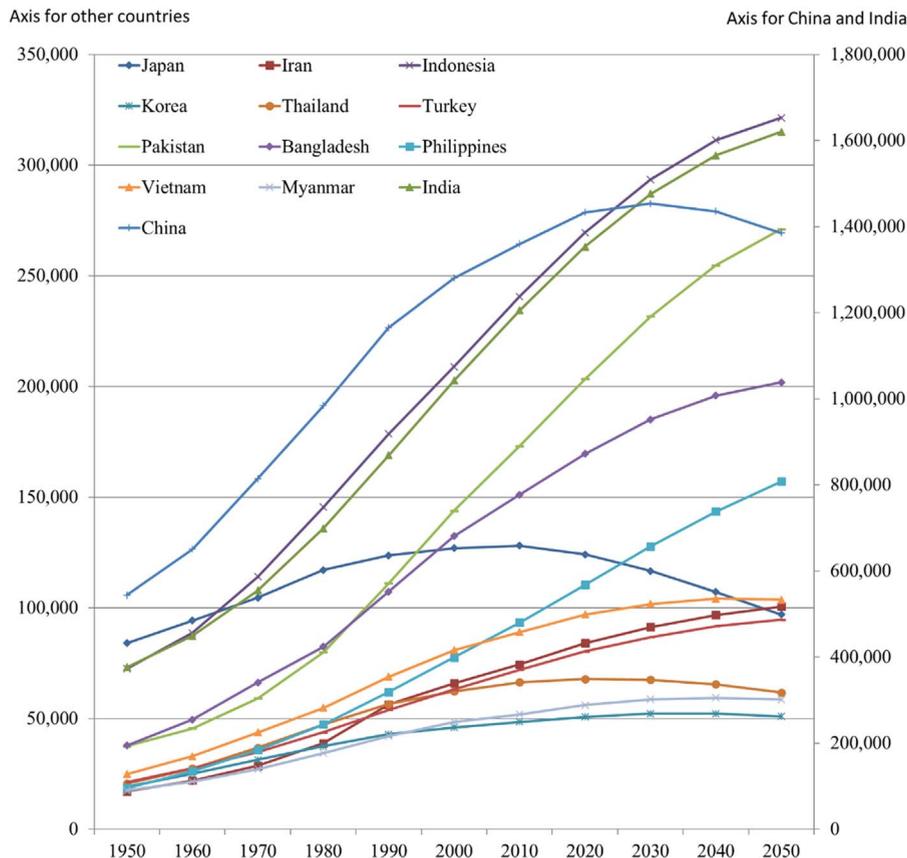


Fig. 1. Population change in Asia (1000 persons).
Source: UN, World Population Prospects: 2012 Revision

called '*new urban world*'; see Kourtit (2015)). Thus, population decline and urbanization rise appear to become two parallel phenomena. Consequently, the position of cities is becoming more strategic in this new and dynamic societal development.

We live nowadays in the '*urban century*', in which the role of urban systems is becoming more and more dominant. The megatrend of structural population concentration in urban areas does clearly not come to a standstill, even not in a depopulating nation like Japan. The unprecedented increases in urban population in Japan - and all over the world - have close links with the magnet position and the economic performance of cities. And therefore, it is important to assess the real socio-economic performance of urban agglomerations. An urban agglomeration comprises not only the central city, but also its suburban areas that form a functional unity with the city concerned.

There is an avalanche of literature on the driving forces of urban agglomerations (see for an overview Barufi and Kourtit (2015)). Most explanations for the emergent dominance of cities and urban agglomerations stem from economic arguments related to spatial-economic externalities. But it should be added that also sociological explanations (ranging from Weber (1947) to Sassen (1991)) and institutional explanations (see Scott (2003)) have been provided to understand the backgrounds and force fields of modern urbanization phenomena.

The growth of cities is historically explained from the presence of agglomeration economies, in particular Marshall-Arrow-Romer (MAR) externalities, Jacobs externalities and Porter externalities. It is also often assumed that such positive returns to scale may be affected by negative externalities, such as environmental pollution, high energy consumption, traffic congestion, etc. Clearly, such negative factors are abundantly present in an urban economy, but if one corrects these phenomena for population size, joint use of alternative energy generation or supply (e.g., CHP, solar installations, etc.), or degree of technological innovation, one often finds that urban agglomerations are rather efficient ecological entities, compared to a completely dispersed pattern of the population.

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, Nijkamp & Scholten, 2011; Kourtit, Nijkamp & Arribas-Bel, 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 standpoint based on various quantitative models (Qiu, Xu & Zhang, 2015, Hao, Zhu & Zhong (2015), Saaty & Sagir, 2015, Guan & Peter G. Rowe, 2016 and Lalehpour (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, Cooper & Rhodes, 1978](#); [Suzuki & Nijkamp 2017a, 2017b](#)). DEA has become an important performance method. This approach will be adopted here, be it in various adjusted forms.

DEA has become an established quantitative assessment tool in the evaluation literature. [Seiford \(2005\)](#) mentions that there are at least 2800 published articles on DEA in various management and planning fields, but nowadays this number is already much higher. The DEA methodology has also expanded its scope towards other disciplines. Currently, in the urban 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.

Various introductions into DEA and applications to city efficiency rankings can be found in [Borger and Kerstens \(1996\)](#), [Worthington and Dollery \(2000\)](#), [Afonso and Fernandes \(2006\)](#), [Suzuki, Nijkamp, and Rietveld \(2008\)](#), [Nijkamp and Suzuki \(2009\)](#), [Kourtit, Nijkamp, and Suzuki \(2013\)](#) and [Suzuki and Nijkamp \(2017b\)](#). 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 also [Suzuki, Nijkamp, Rietveld & Pels, 2010](#)). 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, Korhonen, and Wallenius \(1998\)](#), [Halme, Joro, Korhonen, Salo, and Wallenius \(1999\)](#), [Frei and Harker \(1999\)](#), [Korhonen and Siljamäki \(2002\)](#), [Korhonen, Stenfors, and Syrjänen \(2003\)](#), [Silva, Castro and Thanassoulis \(2003\)](#), [Lins, Angulo-Meza, and Moreira da Silva \(2004\)](#), [Washio, Yamada, Tanaka, and Tanino \(2012\)](#), and [Yang and Morita \(2013\)](#) also proposed 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 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. As mentioned earlier, 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, Nijkamp, and Rietveld \(2015\)](#) 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 a TES. Recently, [Suzuki et al. \(2017a\)](#) also developed a new model from a blend of the TO-DFM and a Time-Series (TS) approach which incorporates a multi-temporal time horizon and a stepwise target score to achieve a final target efficiency score so as to generate a more appropriate efficiency-improving projection. This model is also able to incorporate a catch-up effect in the efficiency projection.

However, this initial TS approach assumes that the efficiency frontier is fixed at any time period. But, in reality, efficiency frontiers may vary -and do vary- from year to year. That is to say, the earlier TS approach does not incorporate a frontier shift effect in setting the target improvement level. Therefore, it is desirable to develop a more realistic efficiency improvement projection which includes a dynamic system of target-settings so as to achieve a target improvement level in order to programme more realistic future policy initiatives.

The aim of this paper is now to develop a new multi-period DEA model from a blend of the TO-DFM approach and a dynamic TS approach which incorporates a flexible multi-period perspective and a stepwise target score to achieve a final target efficiency result in order to programme a more appropriate efficiency-improving projection. The above-mentioned Dynamic TO-DFM model will in the present study be applied to a broad efficiency assessment of several large Japanese cities.

The paper is organised as follows. [Section 2](#) summarise briefly our DFM methodology, while [Section 3](#) presents the newly developed model, which is a Dynamic TS model in the framework of a TO-DFM model. Next, [Section 4](#) presents an application of this new methodology to an efficiency study on the economic performance of Japanese cities. Finally, [Section 5](#) draws some conclusions.

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

The standard Charnes et al. (1978) model (abbreviated hereafter as the CCR-input model) for a given DMU_j (j = 1, ..., 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 Suzuki & Nijkamp, 2017b):

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

where θ represents an objective variable function (efficiency score); x_{mj} is the volume of input m ($m = 1, \dots, M$) for DMU_j ($j = 1, \dots, J$); y_{sj} is the output s ($s = 1, \dots, S$) 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:

$$\hat{x}_k = \theta^* x_k - s^{-*}; \tag{2}$$

$$\hat{y}_k = y_k + s^{+*} \tag{3}$$

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 Fig. 2).

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 Fig. 2 ($\theta^* = OC'/OC$).

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 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 & Nijkamp, 2017b).

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:

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

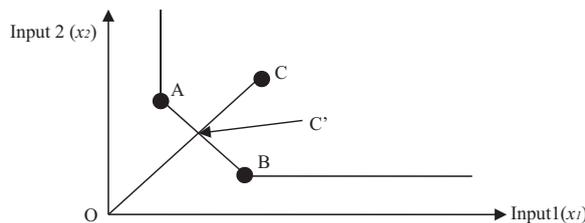


Fig. 2. Illustration of original DEA projection in input space.

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

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

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

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

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

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

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 $(1-\theta^*)$. The input and the output side contribute according to their initial levels 1 and θ^* , implying shares $\theta^*/(1+\theta^*)$ and $1/(1+\theta^*)$ in the improvement contribution. Clearly, the contributions from both sides equal $(1-\theta^*)[\theta^*/(1+\theta^*)]$, and $(1-\theta^*)[1/(1+\theta^*)]$. Hence, we derive for the input reduction targets and the output augmentation targets the following expressions:

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

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

An illustration of this approach is given in Fig. 3.

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 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 Fig. 4). This approach has functioned as an ingredient for many recent DEA studies by the authors of this paper.

3. Design of a dynamic TO-DFM model

Many urban policy strategies call for a multi-temporal perspective, so that appropriate adjustments can be made before the end of the programming horizon.

The Dynamic TO-DFM model designed in the present study comprises the following steps:

Step 1. The final Target Efficiency Score during the target achievement period P in period $p = 0$ (i.e., the origin period) for DMU_k (hereafter FTES^P) is set arbitrarily by the decision- or policy-maker. The improvement projections are divided into two types, depending on the score of the FTES^P as follows:

- $\theta_0^* < \text{FTES}^P < 1.000$; *Non-Attainment* DFM projection (score does not reach the efficiency frontier). This may make sense for DMUs that are far below the efficiency frontier;

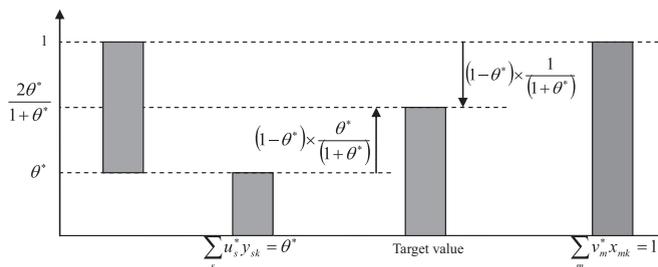


Fig. 3. DFM model with an illustration of the relative contribution of inputs and outputs to closing the efficiency gap.

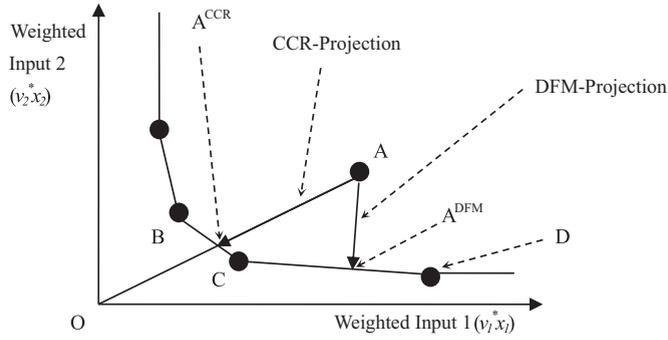


Fig. 4. Degree of improvement of the DFM and the CCR projection in weighted input space.

- $FTES^P = 1.000$; Normal DFM projection (solution just reaches the efficiency frontier);

where θ_0^* is an efficiency score for DMU_k in period 0.

Step 2. The Total Efficiency Gap at the target achievement time P for DMU_k in period 0 (hereafter TEG_0^P) is calculated by formula (15):

$$TEG_0^P = FTES^P - \theta_0^* \tag{15}$$

The Target Efficiency Score at any arbitrary period t (t=1, 2, ..., P) for DMU_k in period 0 (hereafter TES_0^t) is calculated by formula (16):

$$TES_0^t = \theta_0^* + \frac{t}{P} \times TEG_0^P \tag{16}$$

The $FTES^P$, TEG_0^P and TES_0^t values at an arbitrary period t (t=1, 2, ..., P) in period 0 are illustrated in Fig. 5.

Step3. Solve $TES_0^t = \frac{\theta_0^* + MP_0^t(1 - \theta_0^*) \times \frac{\theta_0^*}{(1 + \theta_0^*)}}{1 - MP_0^t(1 - \theta_0^*) \times \frac{1}{(1 + \theta_0^*)}}$. (17)

The essence of formula (17) is closely associated with formula (11) and (12). The numerator is formed by output augmentation targets that correspond to formula (22), while the denominator is the input reduction target corresponding to formula (21), in formula (17), so as to reach TES_0^t . Then, we get MP_0^t , which is a Magnification Parameter of TES_0^t . MP_0^t assumes an intermediate role by adjusting the input reduction target and the output augmentation target in formulas (20) and (21) in order to ensure an alignment of the TES_0^t and DFM projection score for DMU_k .

Step 4. Solve the Dynamic TO-DFM model using formulas (18)–(25). Then, an optimal input reduction value and output increase value to reach a TES_0^t can be calculated as follows:

$$\min Fr^x = \sqrt{\sum_m (v_m^* x_{mk} - v_m^* d_{mk}^t)^2}; \tag{18}$$

$$\min Fr^y = \sqrt{\sum_s (u_s^* y_{sk} - u_s^* d_{sk}^t)^2}; \tag{19}$$

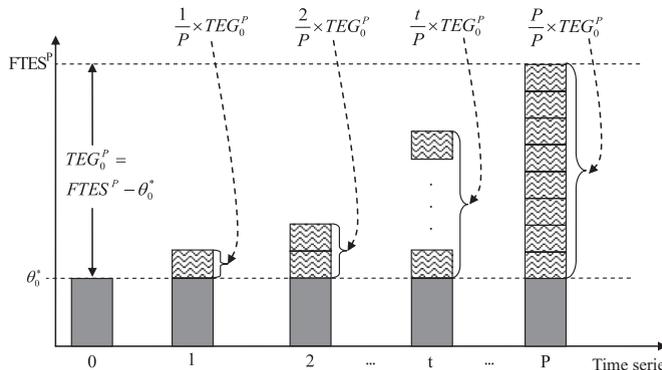


Fig. 5. Illustration of the $FTES^P$, TEG_0^P and TES_0^t at arbitrary period t in period 0.

$$\text{s.t. } TES_0^t = \frac{\sum_s u_s^*(y_{sk} + d_{sk}^{yt})}{\sum_m v_m^*(x_{mk} - d_{mk}^{xt})}; \tag{20}$$

$$\sum_m v_m^*(x_{mk} - d_{mk}^{xt}) = 1 - MP_0^t(1 - \theta_0^*) \times \frac{1}{(1 + \theta_0^*)}; \tag{21}$$

$$\sum_s u_s^*(y_{sk} + d_{sk}^{yt}) = \theta_0^* + MP_0^t(1 - \theta_0^*) \times \frac{\theta_0^*}{(1 + \theta_0^*)}; \tag{22}$$

$$x_{mk} - d_{mk}^{xt} \geq 0; \tag{23}$$

$$d_{mk}^{xt} \geq 0; \tag{24}$$

$$d_{sk}^{yt} \geq 0. \tag{25}$$

Step.3 and Step.4 are of course repetitive computations using the values $t = 1, 2, \dots, P$.

Step.5 Now, we make a shift to period p ($p = 1, 2, \dots, P$).

Calculate an efficiency score for DMU_k in period p based on a dataset for all DMUs in period p . We then get θ_p^* for DMU_k . The ‘Total Efficiency Gap’ at the target achievement time P for DMU_k in period p (hereafter TEG_p^P) is calculated by formula (26):

$$TEG_p^P = FTES^P - \theta_p^*. \tag{26}$$

The Target Efficiency Score at any arbitrary period t ($t = 1, 2, \dots, P$) for DMU_k in period p (hereafter TES_p^t) is calculated by formula (27):

$$TES_p^t = \theta_p^* + \frac{(t - p)}{(P - p)} \times TEG_p^P. \tag{27}$$

TEG_p^P and TES_p^t at an arbitrary time t ($t = 1, 2, \dots, P$) in period p are illustrated in Fig. 6 (this is an example in the case of $p = 1$).

From Fig. 6, we notice that $\theta_0^* + \frac{1}{P} \times TEG_0^P \neq \theta_1^*$ in t (and period p) = 1. This means that there is a gap between the target improvement efficiency score at period 1 in period 0 ($\theta_0^* + \frac{1}{P} \times TEG_0^P$) and the real improved efficiency score in period 1 (θ_1^*). Of course, this might coincidentally be in accordance with these values, but this may be considered as an extremely rare case. Therefore, we need to adjust a target efficiency score incorporating these gaps to set an adjusted target in the next period in order to reach a FTES in the target achievement period P . This adjustment is described here as a difference between TEG_1^P and TEG_0^P .

We also notice that $\theta_1^* - \theta_0^*$ includes both a catch-up effect and a frontier-shift effect. That is to say, our new Dynamic TO-DFM model can incorporate these two effects in the efficiency improvement projection.

$$\text{Step 6. Solve } TES_p^t = \frac{\theta_p^* + MP_p^t(1 - \theta_p^*) \times \frac{\theta_p^*}{(1 + \theta_p^*)}}{1 - MP_p^t(1 - \theta_p^*) \times \frac{1}{(1 + \theta_p^*)}}. \tag{28}$$

Then, we get MP_p^t , which is a Magnification Parameter of TES_p^t . MP_p^t assumes an intermediate role by adjusting the input reduction target and the output increase target in formulas (32) and (33) in order to ensure an alignment of the TES_p^t and DFM projection score for DMU_k .

Step 7. Solve the Dynamic-TO-DFM model using formulas (29)–(36); then, an optimal input reduction value and output increase value to reach a TES_p^t can be calculated as follows:

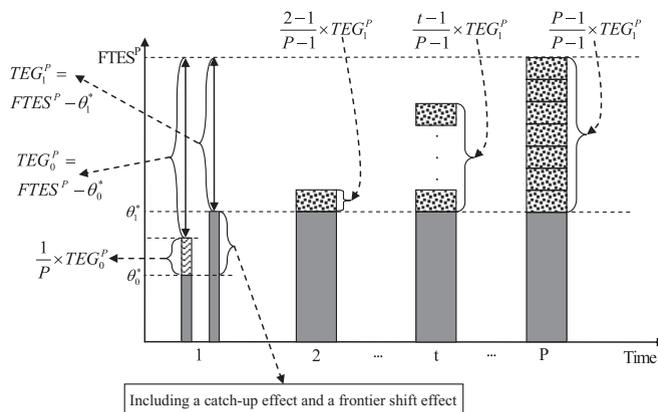


Fig. 6. Illustration of the FTES^P, TEG_p^P and TES_p^t at arbitrary period t (in the case of period 1).

$$\min Fr^x = \sqrt{\sum_m (v_m^* x_{mk} - v_m^* d_{mk}^{xt})^2}; \tag{29}$$

$$\min Fr^y = \sqrt{\sum_s (u_s^* y_{sk} - u_s^* d_{sk}^{yt})^2}; \tag{30}$$

$$\text{s.t. } TES_p^t = \frac{\sum_s u_s^* (y_{sk} + d_{sk}^{yt})}{\sum_m v_m^* (x_{mk} - d_{mk}^{xt})}; \tag{31}$$

$$\sum_m v_m^* (x_{mk} - d_{mk}^{xt}) = 1 - MP_p^t (1 - \theta_p^*) \times \frac{1}{(1 + \theta_p^*)}; \tag{32}$$

$$\sum_s u_s^* (y_{sk} + d_{sk}^{yt}) = \theta_p^* + MP_p^t (1 - \theta_p^*) \times \frac{\theta_p^*}{(1 + \theta_p^*)}; \tag{33}$$

$$x_{mk} - d_{mk}^{xt} \geq 0; \tag{34}$$

$$d_{mk}^{xt} \geq 0; \tag{35}$$

$$d_{sk}^{yt} \geq 0. \tag{36}$$

Step 6 and Step 7 are repeated computations using the values $t = 1, 2, \dots, P$.

Step 8. Period p makes a shift to period P ; then the Dynamic-TO-DFM model is completed.

Step 9. Decision – or policy– makers may next conduct a feasibility analysis for these improvement plans. If the plan proposed still remains out of reach at p , then the decision – or policy– maker may set an adjusted Final Target Efficiency Score at the target achievement period P , like $FTES_{Adjustment}^P$. Then Step 2 to Step 7 are again repeated computations.

An illustration of the TS-TO-DFM model is given in Fig. 7, while an illustration of the Dynamic TO-DFM model is given in Fig. 8.

From Fig. 7, we notice that our TS-TO-DFM model assumes that the efficiency frontier is fixed at any time period. That is to say, the TS approach does not incorporate a frontier-shift effect in setting the target improvement level, as shown in Fig. 7.

In contrast, from Fig. 8 we notice that a new Dynamic TO-DFM model includes both a frontier shift-effect and a catch-up effect of target-settings to achieve a target improvement level in order to programme more realistic policy initiatives, as is suggested in Fig. 8.

4. An evaluation of the economic performance of Japanese cities

4.1. Database and analytical framework

As mentioned at the beginning, recent population and economic changes in urban systems in Japan call for a careful policy assessment of cities. For our empirical analysis we use a set of relevant input and output data from 2007 to 2013 for a set of 16 Japanese big cities (so-called government-ordinance-designated cities, in Japan) in order to evaluate and compare their broad economic efficiency. The DMUs used in our analysis are listed in Table 1. We note that Sagamihara, Sakai, Okayama and Kumamoto are also government-ordinance-designated cities we note that at present, but these cities were announced officially only after 2007 (while the GRP data of Sakai city were undocumented from 2007 to 2013). Consequently, these cities were omitted from the list, for reasons of institutional change of the executive authority and data restrictions.

For our comparative analysis of these 16 cities, we consider two Inputs (I):

- (I1) Population (Reference: population data from the Basic Resident Register in Japan; source: data acquisition from each city’s website);
- (I2) City budget (Reference: Ministry of Internal Affairs and Communications; source: Statistical Yearbook of Local Government

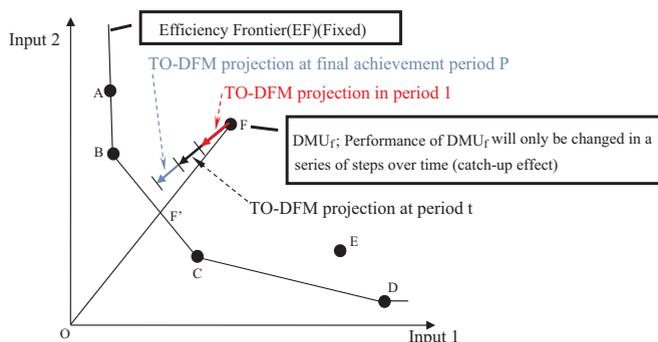


Fig. 7. Illustration of TS-TO-DFM model.

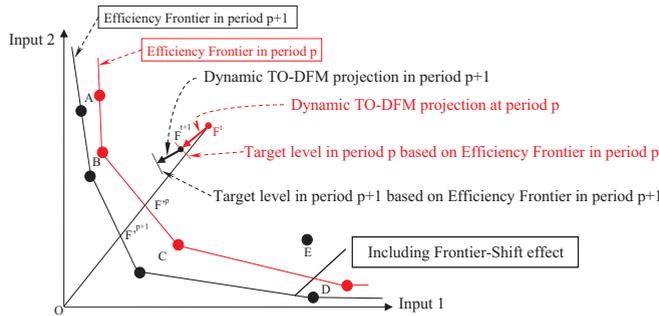


Fig. 8. Illustration of Dynamic TO-DFM model.

Table 1
A list of Japanese big cities.

No	City	No	City
1	Sapporo	9	Hamamatsu
2	Sendai	10	Nagoya
3	Saitama	11	Kyoto
4	Chiba	12	Osaka
5	Yokohama	13	Kobe
6	Kawasaki	14	Hiroshima
7	Niigata	15	Kitakyushu
8	Shizuoka	16	Fukuoka

Finance 2007–2013. <http://www.soumu.go.jp/iken/zaisei/toukei.html>)

In our extended DEA model also two Outputs (O) are incorporated:

- (O1) GRP (Gross Regional Product) (Reference: municipal accounts; data acquisition from each city’s website);
 - (O2) Tax revenues (this is tax revenues for local governments; it is composed by independent revenue which is not including a subsidy from the national government)
- (Reference: Ministry of Internal Affairs and Communications, Statistical Yearbook of Local Government Finance 2007–2013, <http://www.soumu.go.jp/iken/zaisei/toukei.html>).

4.2. Efficiency evaluation based on the super-efficiency CCR-I model

The efficiency assessment result for the 16 cities from 2007 to 2013 based on the Super-Efficiency CCR-I model is presented in Fig. 9. Clearly, various cities in Japan have a DEA score above 1.0.

From Fig. 9, it can be seen that Osaka, Nagoya, Kawasaki and Saitama in 2013 may be regarded as super-efficient cities. Osaka city is central to the vitality of the Kansai regional economy, while Nagoya city is essential for the vitality of the manufacturing hub in Japan. Kawasaki and Saitama are situated in the Tokyo metropolitan area. Furthermore, these cities are characterized by a maximum population density, as shown in Table 2.

As a next step in our study, we have carried out a correlation analysis between population density and DEA scores, as shown in Fig. 10.

The coefficient of correlation in Fig. 10 is 0.756, while, in particular, it shows a statistical significance (P value is 0.000697, significant at a 1% level). From these facts, we can infer that these cities have a prerogative of economic, geographical and population density.

It can also be seen that the efficiency scores of Sendai 2011 decline drastically compared to their 2010 score. It is plausible that this reflects the serious impact of the Great East Japan Earthquake in 2011. We also notice that Sapporo city has the lowest efficiency scores. Sapporo city may also suffer from an indirect influence of the earthquake from 2011. Sightseeing (e.g., nature) is one of the main industries of Sapporo in Hokkaido prefecture (total tourist income of Hokkaido in 2015 is 1.43 trillion Yen, while total economic ripple effect is 2.09 trillion Yen. More detail, see report from Hokkaido prefecture; http://www.pref.hokkaido.lg.jp/kz/kkd/toukei/6th_Economic_impacts_research_20170922_58.pdf).

The number of total tourism visitors to Hokkaido is ranked secondly among all prefectures in Japan. A time-series comparison of the number of visitors to Hokkaido is shown in Fig. 11. From Fig. 11, we notice that the number of visitors show a steep decline in 2011, as a result of a negative effect of radiation contamination by the Fukushima nuclear accident.

It seems thus necessary to make a serious effort to improve the urban economic performance of this city. We will now address here in particular the city of Sapporo.

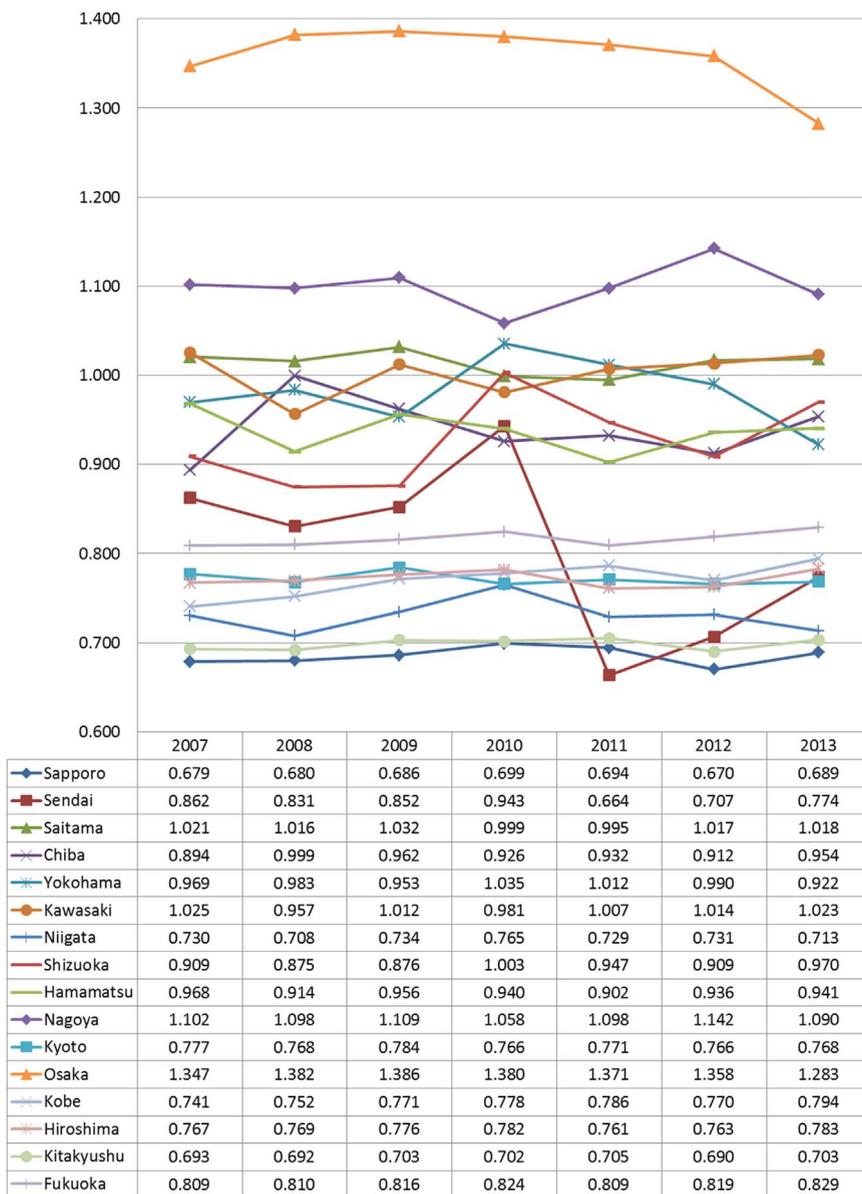


Fig. 9. Efficiency scores for Japanese big cities based on the SE-CCR-I model.

4.3. Efficiency improvement projection based on the TS-TO-DFM model and the Dynamic TO-DFM model for Sapporo

Next, the above-mentioned Dynamic TO-DFM model is used to analyse realistic circumstances and to determine the requirements for an operational strategy for a feasible efficiency improvement in Sapporo city. We will use Sapporo 2007 as an illustrative case and point of reference, and present an efficiency-improvement projection result based on the TS-TO-DFM model and the Dynamic TO-DFM model as shown in Fig. 12. The 2007 DEA efficiency value for Sapporo is 0.679, and we set the origin period $p = 0$ at the year 2007.

We now consider a target achievement time P of 6 (i.e., 2013), while the steps necessary to improve efficiency are given by the time series $t = 1, 2, 3, 4, 5$, and 6 (i.e. 2008, 2009, 2010, 2011, 2012, and 2013).

In generally, the final TES may be set by a policy- or decision-maker based on public promises or the actual economic situation. Our new model maintains flexibility of the value setting by such changing situations. However, if the final TES may require a new value setting in an objective way, we may propose a one-objective rule as follows:

Rule 1. If an efficiency score of target DMU in origin period $p = 0$ falls below an average efficiency score of inefficient DMUs at the origin period $p = 0$, then FTES is set as this average efficiency score of inefficient DMUs considering attainable and realistic

Table 2
List of population density.
(Source: Kawasaki city web site, Comparison of large cities based on national population census 2015, <http://www.city.kawasaki.jp/170/cmsfiles/contents/0000075/75504/h27kokucho-daitoshi.pdf>)

	population density
Sapporo	1742.5
Sendai	1376.3
Saitama	5814.5
Chiba	3579
Yokohama	8517.1
Kawasaki	10316.8
Niigata	1115.7
Shizuoka	499.5
Hamamatsu	512.3
Nagoya	7033.5
Kyoto	1781.2
Osaka	11952.1
Kobe	2760.9
Hiroshima	1317.7
Kitakyushu	1955.1
Fukuoka	4480.5

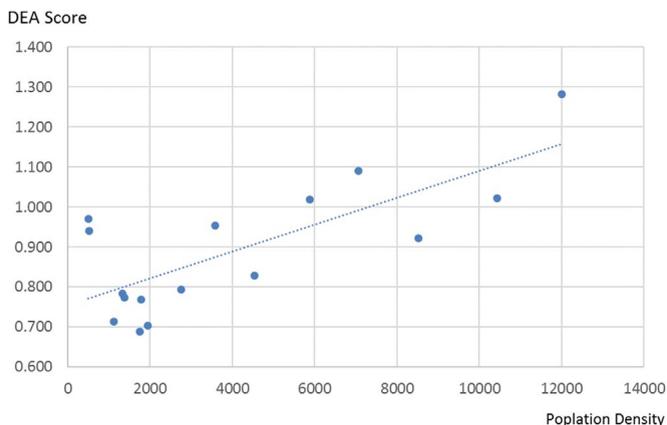


Fig. 10. Correlation analysis between population density and DEA score.

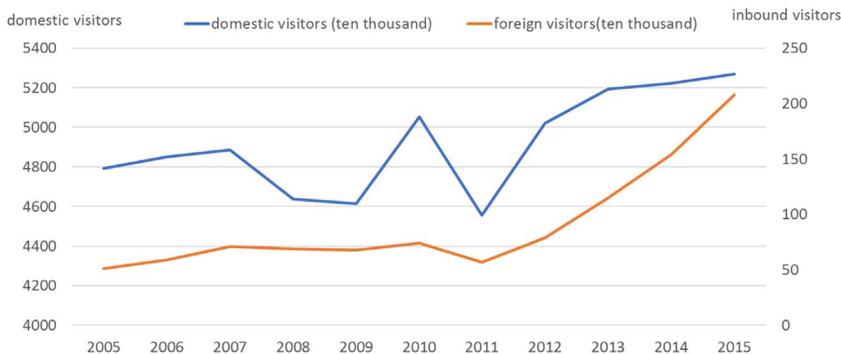


Fig. 11. Time-series comparison of the number of visitors in Hokkaido.
(Source: Report of the Tourist Bureau, Economic Department, Hokkaido Government: Report on Survey on Number of Tourists in Hokkaido, 2015).

goals.

Rule 2. If an efficiency score of target DMU in origin period $p = 0$ is reached above an average efficiency score of inefficient DMUs and below an average efficiency score of all DMUs (i.e. including efficient DMUs) in the origin period $p = 0$, then FTES is set at this average efficiency score of all DMUs considering attainable and realistic policy goals.

Rule 3. If an efficiency score of target DMU in origin period $p = 0$ exceeds the average efficiency score of all DMUs (i.e. including

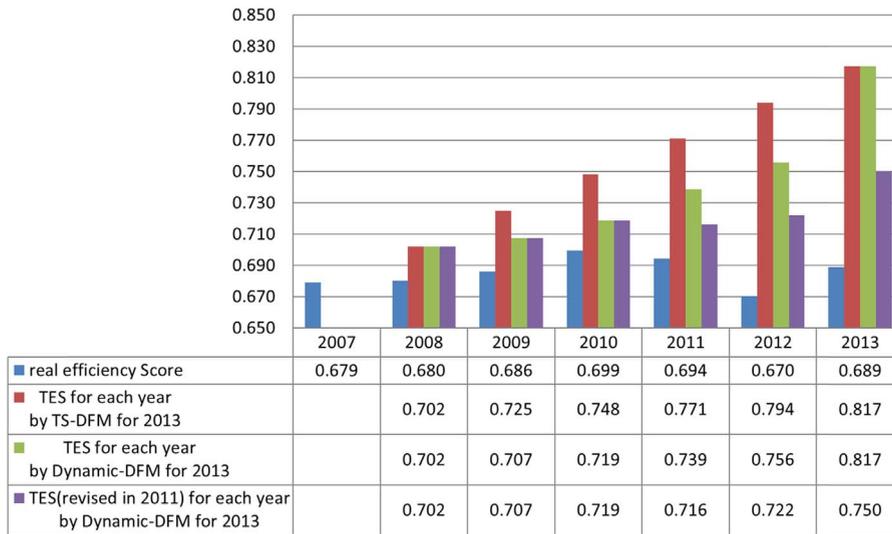


Fig. 12. Efficiency score and Target Efficiency Score (TES) for each year in Sapporo.

efficient DMUs) in origin period $p = 0$, then FTES is set at 1.000 (i.e., a completely achieved efficiency frontier).

Based on above mentioned rules, we present now each target score of Rule 1 to 3 in the final TES for Sapporo 2013, as shown in Table 3.

In this case, the efficiency score for Sapporo at $p=0$ (2007) is 0.679, while the average efficiency score of inefficient DMUs is equal to 0.817. This case becomes an adapted Rule 1, when final TES is set 0.817.

Based on this final TES, each TES for each year calculated by the TS-TO-DFM model and the Dynamic TO-DFM model is shown in Fig. 12. Especially the TES for each year calculated by the Dynamic TO-DFM model represents a frontier shift effect, as shown in Fig. 8. The resulting input reduction values and the output increase values for Sapporo city, based on the TS-TO-DFM model and the Dynamic TO-DFM model, are presented in Figs. 13 and 14.

From Fig. 13, we notice that the projection results of the TS-TO-DFM model seem to be linearly increasing values in a rather simplistic form year by year.

In contrast, from Fig. 14 we notice that the projection results of the Dynamic TO-DFM model seem to reflect a frontier-shift effect for each year, so as to reach a score of 0.817 in 2013. We also notice that the TES from 2011 to 2013 might represent an unrealistic situation, as it does not incorporate the influence of the Great East Japan Earthquake in 2011. In fact, the efficiency score of Sapporo from 2011 to 2013 appears to clearly drop to a lower value, as shown in Fig. 9. In this regard, the Dynamic TO-DFM model can incorporate an adjusted FTES as Step 9 in Section 3, based on these facts and real-world conditions. In the present study, we assume a $FTES_{Adjustment}^{2013}$ set at 0.750, while each target score is set for each year from 2011 to 2013 in Fig. 12. The result of this revised Dynamic target TO-DFM model is presented in Fig. 15.

Table 3
Average score for each rule in $p=0$ (2007).

	Average efficiency score of inefficient DMUs	Average efficiency score of all DMUs
Sapporo	0.679	0.679
Sendai	0.862	0.862
Saitama	Efficient DMU	1.021
Chiba	0.894	0.894
Yokohama	0.969	0.969
Kawasaki	Efficient DMU	1.025
Niigata	0.730	0.730
Shizuoka	0.909	0.909
Hamamatsu	0.968	0.968
Nagoya	Efficient DMU	1.102
Kyoto	0.777	0.777
Osaka	Efficient DMU	1.347
Kobe	0.741	0.741
Hiroshima	0.767	0.767
Kitakyushu	0.693	0.693
Fukuoka	0.809	0.809
Ave.	0.817	0.893

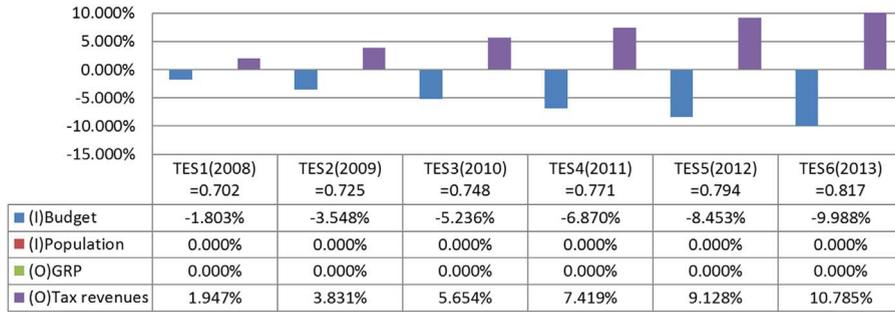


Fig. 13. Efficiency-improvement projection results based on the TS-TO-DFM model (Sapporo).

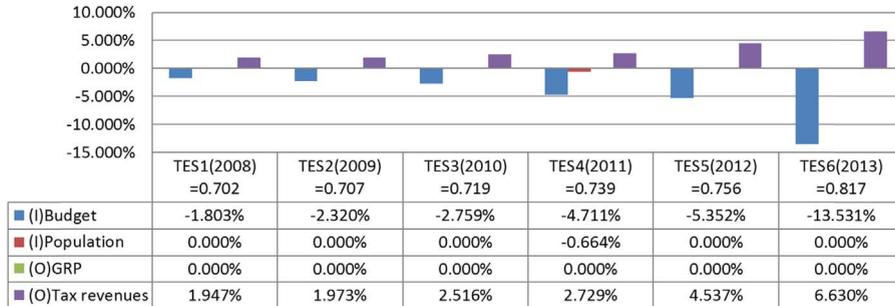


Fig. 14. Efficiency-improvement projection results based on the Dynamic-TO-DFM model. (Sapporo, Rule 1 representative, FTES=0.817).

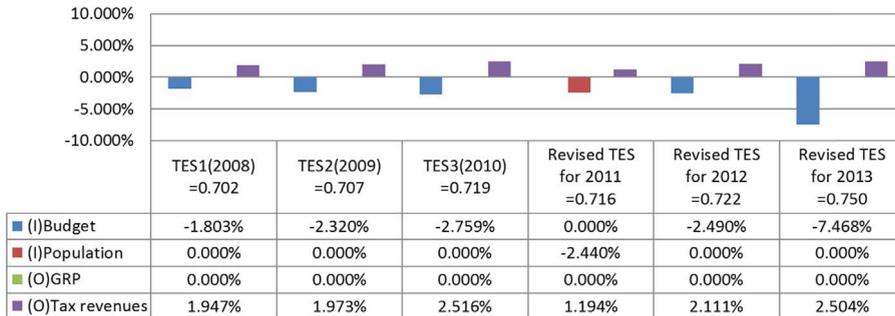


Fig. 15. Efficiency-improvement projection results based on the revised target Dynamic TO-DFM model (Sapporo, Rule 1 representative, Revised FTES=0.750).

From Fig. 15, it is noteworthy that the Dynamic TO-DFM model shows the characteristics of flexibility and implementability in urban policy programmes.

In this study, some other cases corresponding to Rule 2 and 3 are set, namely Sendai (Score 0.862) and Chiba (Score 0.894), respectively. The resulting input reduction values and the output increase values for Sendai and Chiba city based on the Dynamic TO-

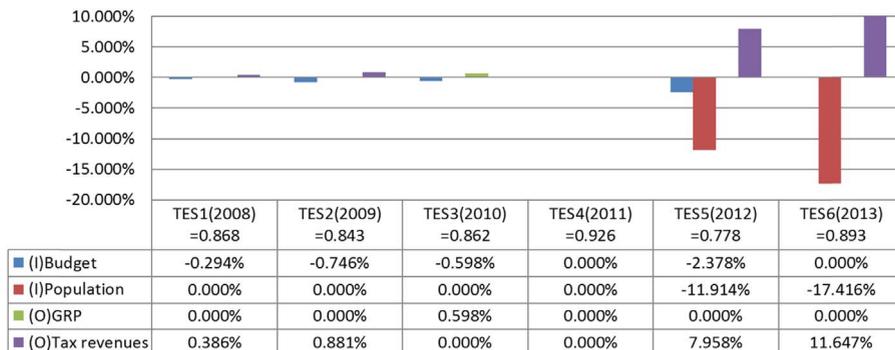


Fig. 16. Efficiency-improvement projection results based on the Dynamic-TO-DFM model. (Sendai, Rule 2 representative, FTES=0.893).

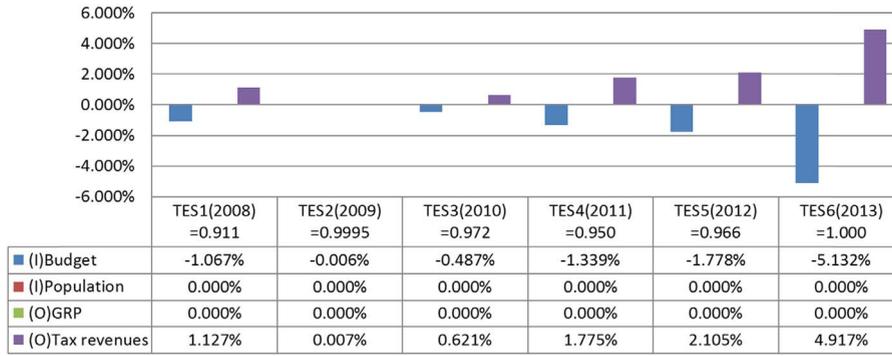


Fig. 17. Efficiency-improvement projection results based on the Dynamic-TO-DFM model. (Chiba, Rule 3 representative, FTES=1.000).

DFM model are presented in Figs. 16 and 17.

5. Conclusion

In this paper, we have presented an empirical assessment framework and applied findings on economic efficiency of Japanese big cities. From these results, it is clear that Osaka, Nagoya, Kawasaki and Saitama may be regarded as super-efficient cities. These cities have a characteristic that is essential for the vitality of the regional economy and the manufacturing hub in Japan, situated in the Tokyo metropolitan area. These facts highlight the impact of spatial attributes to improving a city performance.

Furthermore, this study has demonstrated the statistical significance between city performance and population density. Based on these facts, it supports a policy of population concentration in urban areas, which can improve city performance, even in a depopulating nation like Japan. It is noteworthy that Korea, Thailand, and China will also become depopulating nations in the period 2020 to 2040, and then a policy of population concentration in urban areas may be possible to sustain their economic performance in a future and mature society.

We have here presented a new DEA methodology, the Dynamic TO-DFM model. Its feasibility was tested for improving the economic efficiency of Japanese big cities; the new model was examined on the basis of real-world information on relevant indicators. From the above findings, we note that the Dynamic TO-DFM model is able to present a realistic efficiency-improvement programme which incorporates a stepwise target score in a time-series perspective, frontier shift effects, and real-world conditions so as to achieve a target efficiency score.

In conclusion, our Dynamic TO-DFM model is able to programme a rather realistic efficiency-improvement urban development plan, and may thus provide a meaningful contribution to decision making and planning for efficiency improvement of big cities in Japan, but also for other cities in mature or emerging economies.

Appendix A

A super-efficiency DEA model

In a standard DEA model, all efficient DMUs get by definition a score equal to 1, so that there is no logical way to differentiate between them. This problem has led to focused research to discriminate between efficient DMUs, in order to arrive at an unambiguous ranking, or even a numerical rating of these efficient DMUs, without affecting the results for non-efficiency. In particular, Andersen and Petersen (1993) developed a radial Super-Efficiency model, while, later on, Tone (2001) designed a slacks-based measure (SBM) of super-efficiency in DEA. In general, a Super-Efficiency model aims to identify the relative importance of each individual efficient DMU, by designing and measuring a score for its ‘degree of influence’ if this efficient DMU is omitted from the efficiency frontier (or production possibility set). If this elimination really matters (i.e. if the distance from this DMU to the remaining efficiency frontier is large), and, thus, the firm concerned has a high degree of influence and outperforms the other DMUs, it gets a high score (and is thus super-efficient). Therefore, for each individual DMU a new distance result is obtained, which leads to a new ranking, or even a rating, of all the original efficient DMUs.

Anderson and Petersen (1993) have developed the Super-Efficiency model based on a radial projection (including a CCR model) to arrive at a ranking of all efficient DMUs. The efficiency scores from a super-efficiency model are thus obtained by eliminating the data on the DMU_k to be evaluated from the solution set. For the input model, this can then result in values, which may be regarded, according to the DMU_k, as a state of super-efficiency. These values are then used to rank the DMUs, and, consequently, efficient DMUs may then obtain an efficiency score above 1.000 (see also Suzuki et al. (2015)).

The super-efficiency model based on a CCR-I model can then be written as follows:

$$\min_{\theta, \lambda, s^-, s^+} \theta - es^- - es^+$$

$$\begin{aligned}
 \text{s. t. } \theta x_k &= \sum_{j=1, \neq k}^J \lambda_j x_j + s^- \\
 y_k &= \sum_{j=1, \neq k}^J \lambda_j y_j - s^+ \\
 \lambda_j, s^-, s^+ &\geq 0,
 \end{aligned}
 \tag{A.1}$$

where e is a unit vector $(1, \dots, 1)$, representing a utility factor for all elements. Further details can be found in Suzuki and Nijkamp (2017b).

References

- Afonso, A., & Fernandes, S. (2006). Measuring local government spending efficiency: Evidence for the Lisbon region. *Regional Studies*, 40(1), 39–53.
- Anderson, P., & Petersen, N. (1993). A procedure for ranking efficient units in data envelopment analysis. *Management Science*, 39, 1261–1264.
- Arribas-Bel, D., Nijkamp, P., & Scholten, H. (2011). Multidimensional urban sprawl in Europe: A self-organizing map approach. *Computers, Environment and Urban Systems*, 35(4), 263–275.
- Barufi, A. M., & Kourtit, K. (2015). Agglomeration forces in smart cities. In K. Kourtit, P. Nijkamp, & R. Stough (Eds.). *The Rise of the City - Spatial Dynamics in the Urban Century* (pp. 33–54). Cheltenham: Edward Elgar.
- Borger, B., & Kerstens, K. (1996). Cost efficiency of Belgian local governments: A comparative analysis of FDH, DEA, and econometric approaches. *Regional Science and Urban Economics*, 26(2), 145–170.
- Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, 2, 429–444.
- Cooper, W. W., Seiford, L. M., & Tone, K. (2006). *Introduction to Data Envelopment Analysis and its Uses*. Business Media, Inc: Springer Science.
- Frei, F. X., & Harker, P. T. (1999). Projections on to efficient frontiers: theoretical and computational extensions to DEA. *Journal of Productivity Analysis*, 11(3), 275–300.
- Golany, B. (1988). An interactive MOLP procedure for the extension of DEA to effectiveness analysis. *Journal of the Operational Research Society*, 39, 725–734.
- Grosveld, H. (2002). *The Leading Cities of the World and Their Competitive Advantages* (PhD dissertation) University of Amsterdam.
- Guan, C., & Peter G. Rowe, P. G. (2016). Should big cities grow? Scenario-based cellular automata urban growth modeling and policy applications. *Journal of Urban Management*, 5(2), 65–78.
- Halme, M., Joro, T., Korhonen, P., Salo, S., & Wallenius, J. (1999). A value efficiency approach to incorporating preference information in data envelopment analysis. *Management Science*, 45(1), 103–115.
- Jinwei Hao, J., Zhu, J., & Zhong, R. (2015). The rise of big data on urban studies and planning practices in China: Review and open research issues. *Journal of Urban Management*, 4(2), 92–124.
- Joro, T., Korhonen, P., & Wallenius, J. (1998). Structural comparison of data envelopment analysis and multiple objective linear programming. *Management Science*, 44(7), 962–970.
- Korhonen, P., & Siljamäki, A. (2002). On the use of value efficiency analysis and some further developments. *Journal of Productivity Analysis*, 17(1-2), 49–64.
- Korhonen, P., Stenfors, S., & Syrjänen, M. (2003). Multiple objective approach as an alternative to radial projection in DEA. *Journal of Productivity Analysis*, 20(20), 305–321.
- Kourtit, K. (2015). *The New Urban World, Economic-Geographical Studies on the Performance of Urban Systems*. Poznan: Adam Mickiewicz University (PhD Dissertation).
- Kourtit, K., Nijkamp, P., & Arribas-Bel, D. (2012). Smart cities perspective – a Comparative European Study by Means of Self-organizing Maps, *The European Journal of Social Science Research*, 25(2), 229–246.
- Kourtit, K., Nijkamp, P., & Suzuki, S. (2013). The rat race between world cities: in search of exceptional places by means of super-efficient data envelopment analysis. *Computers, Environment and Urban Systems*, 38, 67–77.
- Lalehpour, M. (2016). Recognition of management structure and spatial planning in tehran metropolitan area. *Journal of Urban Management*, 5(1), 3–15.
- Lins, M. P. E., Angulo-Meza, L., & Moreira da Silva, A. C. (2004). A multi-objective approach to determine alternative targets in data envelopment analysis. *Journal of Operational Research*, 55, 1090–1101.
- Nijkamp, P., & Suzuki, S. (2009). A generalized goals-achievement model in data envelopment analysis: An application to efficiency improvement in local government finance in Japan. *Spatial Economic Analysis*, 4(3), 249–274.
- Qiu, R., Xu, W., & Zhang, Z. (2015). The transformation of urban industrial land use: A quantitative method. *Journal of Urban Management*, 4(1), 40–52.
- Saaty, T. L., & Sagor, M. (2015). Choosing the best city of the future. *Journal of Urban Management*, 4(1), 3–23.
- Sassen, S. (1991). *The Global City*. Princeton NJ: Princeton University Press.
- Scott, A. J. (2003). *The Cultural Economy of Cities*. London: Sage.
- Seiford, L. (2005). *A Cyber-Bibliography for Data Envelopment Analysis (1978–2005)*. CD-ROM in *Introduction to Data Envelopment Analysis and its Uses*. New York: Springer Science, Business Media.
- Silva, M., Castro, P., & Thanassoulis, E. (2003). Finding closest targets in non-oriented DEA models: the case of convex and non-convex technologies. *Journal of Productivity Analysis*, 19, 251–269.
- Suzuki, S., & Nijkamp, P. (2017a). An evaluation of energy-environment-economic efficiency for asian countries: a proposal for a time-series target-oriented dfm model in data envelopment analysis. In A. Batabyal, & P. Nijkamp (Eds.). *Regional Growth and Sustainable Development in Asia* (pp. 113–132). Springer.
- Suzuki, S., & Nijkamp, P. (2017b). *Regional Performance Measurement and Improvement; New Application of Data Envelopment Analysis, New Frontiers in Regional Science: Asian Perspectives 9*. Springer Science + Business Media Singapore.
- Suzuki, S., Nijkamp, P., & Rietveld, P. (2008). Efficiency improvement of city administration management by means of distance friction minimization in data envelopment analysis - an application to government-ordinance-designated cities in Japan-. *Studies in Regional Science*, 38(4), 1041–1053.
- Suzuki, S., Nijkamp, P., & Rietveld, P. (2015). A target-oriented data envelopment analysis for energy-environment efficiency improvement in Japan. *Energy Efficiency*, 8(3), 433–446.
- Suzuki, S., Nijkamp, P., Rietveld, P., & Pels, E. (2010). A distance friction minimization approach in data envelopment analysis: a comparative study on airport efficiency. *European Journal of Operational Research*, 207, 1104–1115.
- Taylor, P. J., Ni, P., Derudder, B., Hoyler, M., Huang, J., Lu, F., Pain, K., Witlox, F., Yang, X., Bassens, D., & Shen, W. (2009). Measuring the world city network: new developments and results. *GaWC Research, Bulletin*, 300.
- Thanassoulis, E., & Dyson, R. G. (1992). Estimating preferred target input-output levels using data envelopment analysis. *European Journal of Operational Research*, 56, 80–97.
- Tone, K. (2001). A slacks-based measure of efficiency on data envelopment analysis. *European Journal of Operational Research*, 498–509.
- Washio, S., Yamada, S., Tanaka, T., & Tanino, T. (2012). Improvements by analyzing the efficient frontier in DEA. *European Journal of Operational Research*, 217, 173–184.
- Weber, M. (1947). *The Theory of Social and Economic Organisation*. London: William Hodge.
- Worthington, A., & Dollery, B., (2000). Efficiency Measurement in the Local Public Sector: Econometric and Mathematical Programming Frontier Techniques, School of Economics and Finance Discussion Papers and Working Papers Series from School of Economics and Finance, Queensland University of Technology, No. 78.
- Yang, X., & Morita, H. (2013). Efficiency Improvement from Multiple Perspectives: An Application to Japanese Banking Industry. *Omega*, 41(3), 501–640.