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

Soushi Suzuki[a] and Peter Nijkamp[b,c]

[a]Hokkai-Gakuen University, Department of Life Science and Technology, 1-1, South26 West 11, Chuo-ku Sapporo 064-0926, Japan
E-mail: soushi-s@lst.hokkai-s-u.ac.jp
[b] Tinbergen Institute, Gustav Mahlerplein 117, 1082 MS, Amsterdam, The Netherlands
[c]A.Mickiewicz University, Poznan, Poland
E-mail: pnijkamp1@gmail..com

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Abstract

This paper aims to provide an advanced dynamic assessment methodology for city performance strategies, based on an extended Data Envelopment Analysis (DEA). The use of this novel efficiency-improving approach based on DEA originates from the earlier developed, so-called Distance Friction Minimisation (DFM) method. To design a feasible and realistic improvement strategy for low-efficiency Decision-Making Units (DMUs), we introduce a Target-Oriented (TO) DFM model on top of a Super-Efficiency model, in order to generate an appropriate efficiency-improving projection model. The standard TO approach specifies a target-efficiency score (TES) for inefficient DMUs. This approach is able to compute an input reduction value and an output increase value in order to achieve a desired TES. To develop a dynamic DEA perspective, we create next a new model from a blend of the TO-DFM approach 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 DEA projection. This new model is able to incorporate a catch-up effect in the efficiency projection. However, the regular TS approach assumes that the efficiency frontier is fixed over any time period. However, in reality, efficiency frontiers vary from year to year. That is to say, the TS approach is not able to incorporate a frontier shift effect in setting the overall target improvement level. Therefore, it is necessary to develop a more realistic efficiency improvement projection which includes a dynamic system of target-settings to achieve a target improvement level so as to programme more realistic policy initiatives. In the present paper we develop a new multi-period model from a blend of the TO-DFM model and a dynamic TS decision approach. 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, due to comparative data limitations, we consider 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 (i.e., "government-ordinance-designated cities") by means of the above described, extended super-efficient DEA model. Finally, we provide an efficiency improvement programme based on the Dynamic TO-DFM model for inefficient cites.

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 same turbulence in the past decades. We will briefly illustrate the dynamics in the Asian countries based on population changes as presented in Figure 1. We have chosen this demographic information, as this is a relatively easy variable to predict over a relatively long time period.

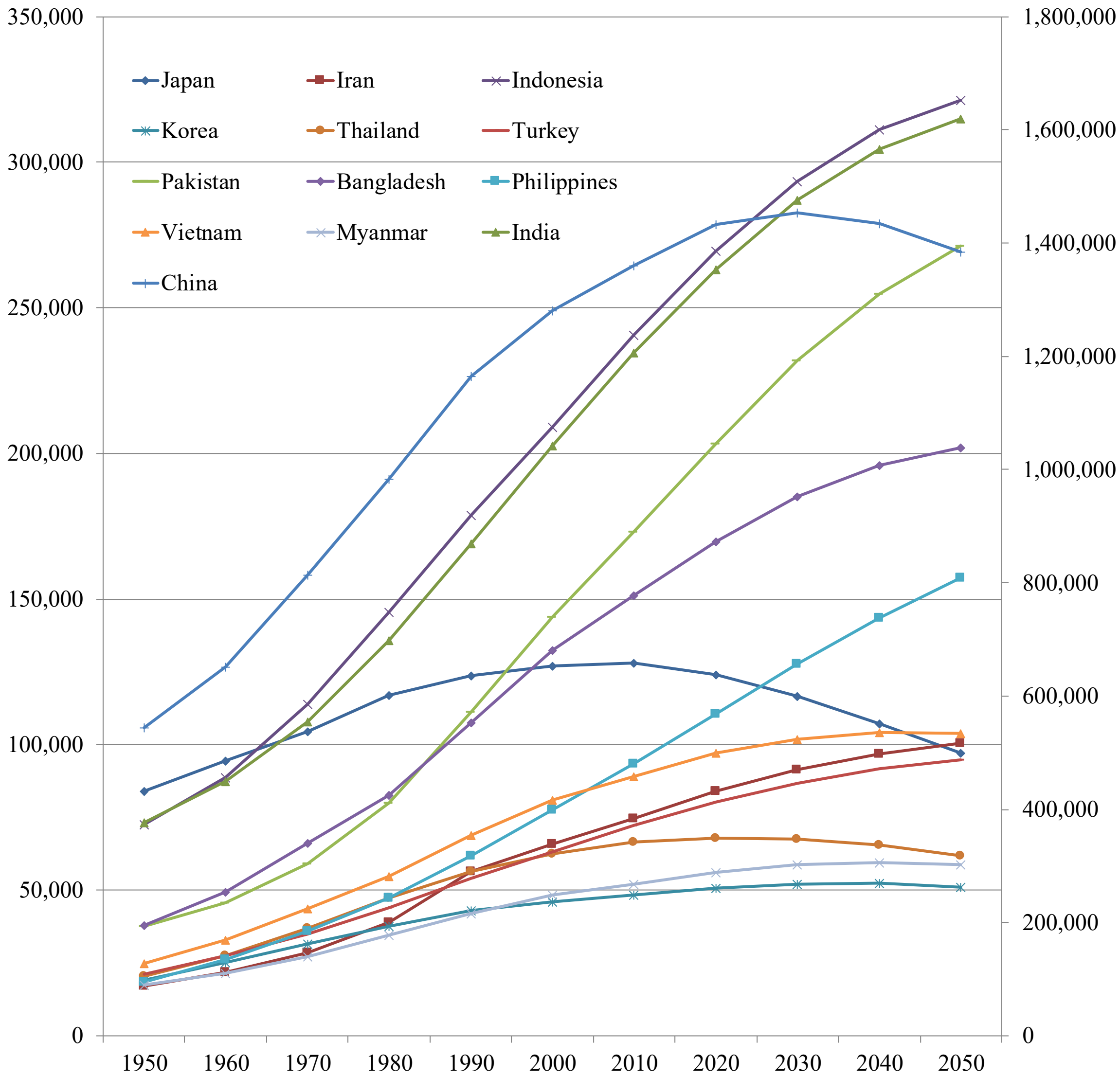


Figure 1 Population change in Asia (1000 persons) Source: UN, World Population Prospects: 2012 Revision

From Figure 1, it can easily be seen that Japan is already in a transition process in wards 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-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 dynamic societal development.

We live nowadays in the '*urban century*'. The role of urban systems is becoming more and more dominant. The megatrend of population concentration in urban areas does clearly not come to a standstill, even not in a depopulating nation like Japan. These 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 performance of urban agglomeration.

A standard tool which is used to judge the performance or efficiency among different actors is Data Envelopment Analysis (DEA), proposed by Charnes, Cooper and Rhodes (1978). Over the past decades, this has become an established quantitative assessment method 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 et al. (1996), Worthington et al. (2000), Afonso et al. (2006), Suzuki et al. (2008), Nijkamp et al. (2009), Kourtit et al. (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 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 et al., 2010). One of the first contributions was made 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 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 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 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. Thus, the 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.

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, even though 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 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 can 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 in order 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 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 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 be applied to a broad efficiency assessment of 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

An efficiency-improvement solution in the original DEA model (abbreviated hereafter as the CCR-input model; see Appendix A1) requires that the input values are reduced radially by a uniform ratio θ^* (θ^*=OD'/OD in Figure A1).

The (v^*, u^*) values obtained as an optimal solution for formula (A.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 (A.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. Thus, the 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 only briefly describe the various steps (for more details, we refer to Suzuki and Nijkamp 2017b).

First, the distance function Fr^x and Fr^y is specified by means of (2.1) and (2.2), 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:

$$\min\ Fr^{x} = \sqrt{\sum_{m}\left(v_m^{*}x_{mk} - v_m^{*}d_{mk}^{x}\right)^2} \tag{2.1}$$

$$\min\ Fr^{y} = \sqrt{\sum_{s}\left(u_s^{*}y_{sk} - u_s^{*}d_{sk}^{y}\right)^2} \tag{2.2}$$

$$\text{s.t.}\quad \sum_{m} v_m^{*}\left(x_{mk} - d_{mk}^{x}\right) = \frac{2\theta^{*}}{1+\theta^{*}} \tag{2.3}$$

$$\sum_{s} u_s^{*}\left(y_{sk} + d_{sk}^{y}\right) = \frac{2\theta^{*}}{1+\theta^{*}} \tag{2.4}$$

$$x_{mk} - d_{mk}^{x} \geq 0 \tag{2.5}$$

$$d_{mk}^{x} \geq 0 \tag{2.6}$$

$$d_{sk}^{y} \geq 0\,, \tag{2.7}$$

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 (2.3) and (2.4) refer to the target values of input reduction and output augmentation.

It is now possible to determine each optimal distance d_{mk}^{x*} and d_{sk}^{y*} by using the MOQP model (2.1) - (2.7). The distance minimisation solution for an inefficient DMU$_k$ can be expressed by means of formulas (2.8) and (2.9):

$$x_{mk}^{*} = x_{mk} - d_{mk}^{x*}\,; \tag{2.8}$$

$$y_{sk}^{*} = y_{sk} + d_{sk}^{y*}\,. \tag{2.9}$$

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 solutions 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 2). This approach has functioned as an ingredient for many recent DEA studies by the authors of this paper.

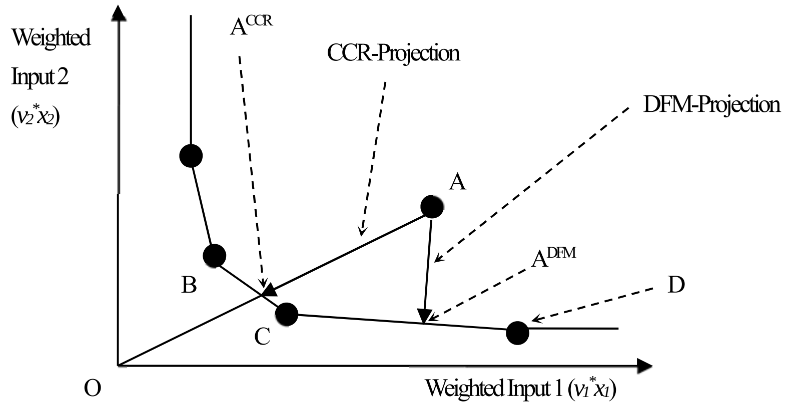


Figure 2 Degree of improvement of the DFM and the CCR projection in weighted input space

3. Design of a Dynamic TO-DFM model

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:

- $\theta_0^* < FTES^P < 1.000$; *Non-Attainment* DFM projection (score does not reach the efficiency frontier). This may make sense for DMUs that are far below the efficiency frontier;
- $FTES^P = 1.000$; *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 (3.1):

$$TEG_0^P = FTES^P - \theta_0^* . \quad (3.1)$$

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 (3.2):

$$TES_0^t = \theta_0^* + \frac{t}{P} \times TEG_0^P . \quad (3.2)$$

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 Figure 3.

Step 3. Solve

$$TES_0^t = \frac{\theta_0^* + MP_0^t\left(1-\theta_0^*\right)\times\dfrac{\theta_0^*}{\left(1+\theta_0^*\right)}}{1 - MP_0^t\left(1-\theta_0^*\right)\times\dfrac{1}{\left(1+\theta_0^*\right)}} . \quad (3.3)$$

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 increase target in formulas (3.7) and (3.8) in order to ensure an alignment of the TES_0^t and DFM projection score for DMU_k.

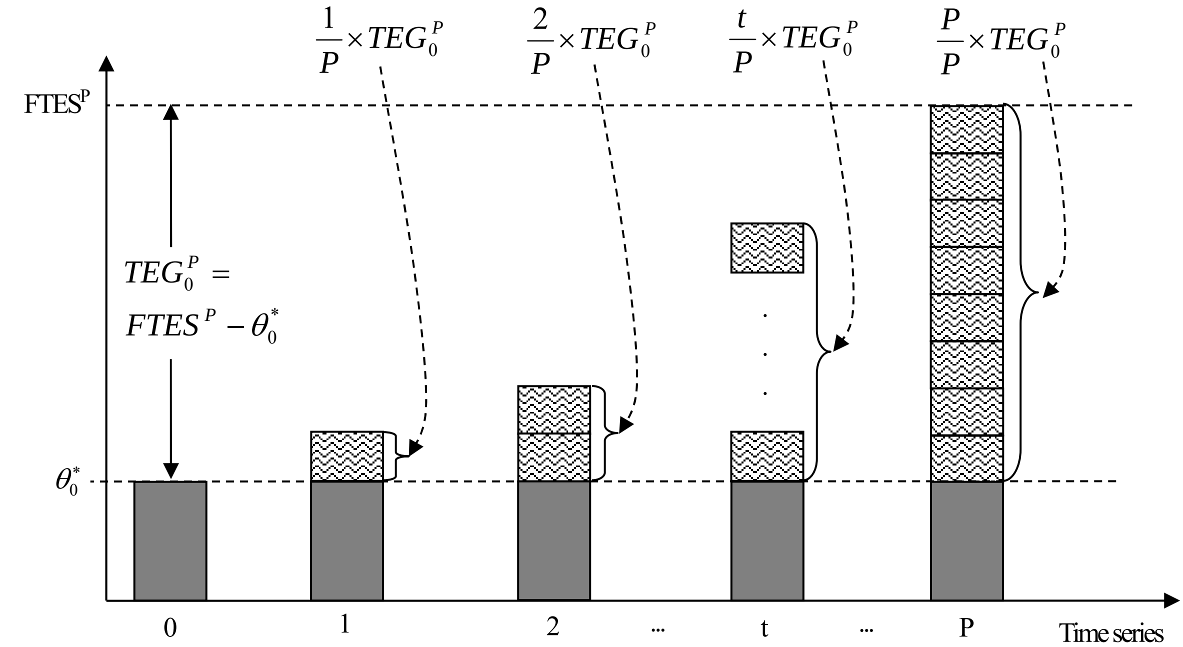


Figure 3 Illustration of the FTES^P, TEG$_0^P$ and TES$_0^t$ at arbitrary period t in period 0

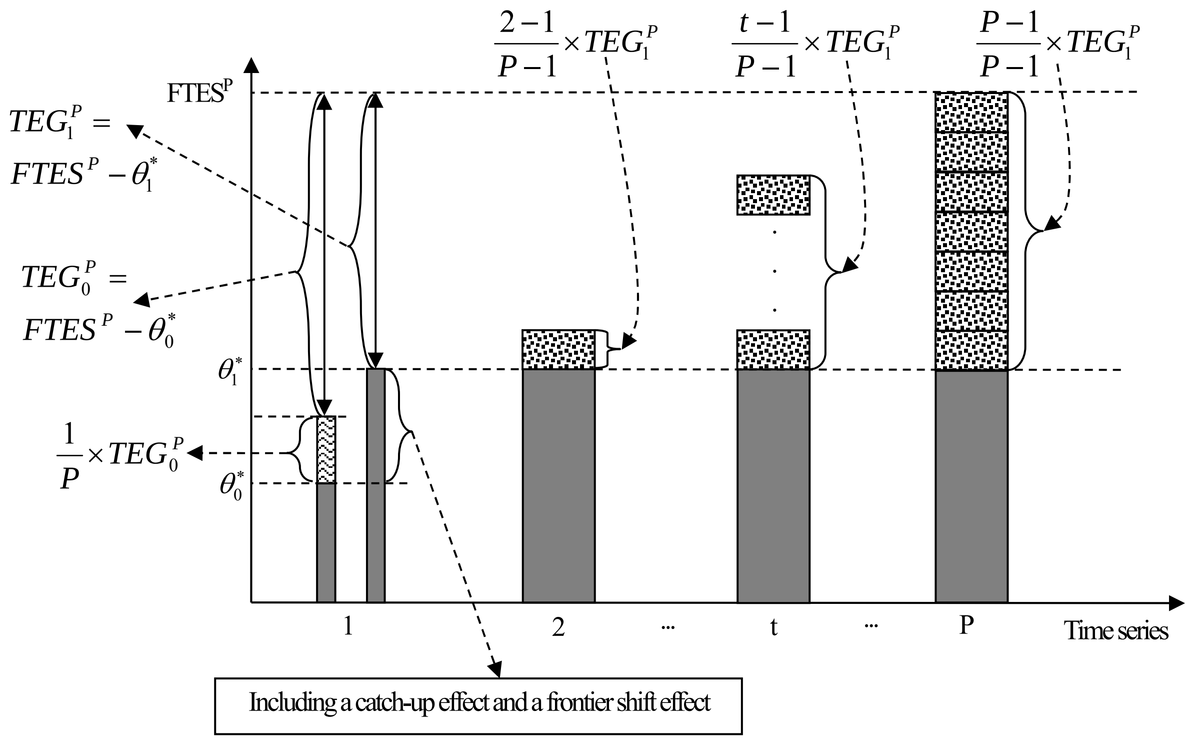


Figure 4 Illustration of the FTES^P, TEG$_p^P$ and TES$_p^t$ at arbitrary period t (in the case of period 1)

Step 4. Solve the Dynamic TO-DFM model using formulas (3.4)–(3.11); then, an optimal input reduction value and output increase value to reach a TES$_0^t$ can be calculated as follows:

$$\min \;\; Fr^x = \sqrt{\sum_m \left(v_m^* x_{mk} - v_m^* d_{mk}^{xt}\right)^2} \;; \tag{3.4}$$

$$\min \quad Fr^y = \sqrt{\sum_s \left(u_s^* y_{sk} - u_s^* d_{sk}^{yt}\right)^2} \; ; \tag{3.5}$$

$$\text{s.t.} \quad TES_0^t = \frac{\sum_s u_s^* \left(y_{sk} + d_{sk}^{yt}\right)}{\sum_m v_m^* \left(x_{mk} - d_{mk}^{xt}\right)} ; \tag{3.6}$$

$$\sum_m v_m^* \left(x_{mk} - d_{mk}^{xt}\right) = 1 - MP_0^t \left(1 - \theta_0^*\right) \times \frac{1}{\left(1 + \theta_0^*\right)} ; \tag{3.7}$$

$$\sum_s u_s^* \left(y_{sk} + d_{sk}^{yt}\right) = \theta_0^* + MP_0^t \left(1 - \theta_0^*\right) \times \frac{\theta_0^*}{\left(1 + \theta_0^*\right)} ; \tag{3.8}$$

$$x_{mk} - d_{mk}^{xt} \geq 0 ; \tag{3.9}$$

$$d_{mk}^{xt} \geq 0 ; \tag{3.10}$$

$$d_{sk}^{yt} \geq 0 . \tag{3.11}$$

Step.3 and Step.4 are repeated computations using the values t = 1, 2, . . ., P.

Step.5 Now we consider to make a shift to period p (p=1, 2, . . ., 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 (3.12):

$$TEG_p^P = FTES^P - \theta_p^* . \tag{3.12}$$

The Target Efficiency Score at an arbitrary period t (t=1, 2, . . ., P) for DMU_k in period p (hereafter TES_p^t) is calculated by formula (3.13):

$$TES_p^t = \theta_p^* + \frac{(t-p)}{(P-p)} \times TEG_p^P . \tag{3.13}$$

TEG_p^P and TES_p^t at an arbitrary time t (t=1, 2, . . ., P) in period p are illustrated in Figure 4 (this is an example in the case of p=1).

From Figure 4, 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 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 Final Target Efficiency Score 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.

Step 6. Solve $$TES_p^t = \frac{\theta_p^* + MP_p^t\left(1-\theta_p^*\right)\times\frac{\theta_p^*}{\left(1+\theta_p^*\right)}}{1 - MP_p^t\left(1-\theta_p^*\right)\times\frac{1}{\left(1+\theta_p^*\right)}}. \tag{3.14}$$

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 (3.18) and (3.19) 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 (3.15)–(3.22); then, an optimal input reduction value and output increase value to reach a TES_p^t can be calculated as follows:

$$\min\ Fr^x = \sqrt{\sum_m \left(v_m^* x_{mk} - v_m^* d_{mk}^{xt}\right)^2}\ ; \tag{3.15}$$

$$\min\ Fr^y = \sqrt{\sum_s \left(u_s^* y_{sk} - u_s^* d_{sk}^{yt}\right)^2}\ ; \tag{3.16}$$

$$\text{s.t.}\quad TES_p^t = \frac{\sum_s u_s^*\left(y_{sk} + d_{sk}^{yt}\right)}{\sum_m v_m^*\left(x_{mk} - d_{mk}^{xt}\right)}; \tag{3.17}$$

$$\sum_m v_m^*\left(x_{mk} - d_{mk}^{xt}\right) = 1 - MP_p^t\left(1-\theta_p^*\right)\times\frac{1}{\left(1+\theta_p^*\right)}; \tag{3.18}$$

$$\sum_s u_s^*\left(y_{sk} + d_{sk}^{yt}\right) = \theta_p^* + MP_p^t\left(1-\theta_p^*\right)\times\frac{\theta_p^*}{\left(1+\theta_p^*\right)}; \tag{3.19}$$

$$x_{mk} - d_{mk}^{xt} \geq 0\,; \tag{3.20}$$

$$d_{mk}^{xt} \geq 0\,; \tag{3.21}$$

$$d_{sk}^{yt} \geq 0\,. \tag{3.22}$$

Step. 6 and Step. 7 are repeated computations using the values t = 1, 2, . . ., 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 $FTES^{P}_{Adjustment}$. Then Step.2 to Step.7 are repeated computations.

An illustration of the TS-TO-DFM model is given in Figure 5, and an illustration of the Dynamic TO-DFM model is given in Figure 6

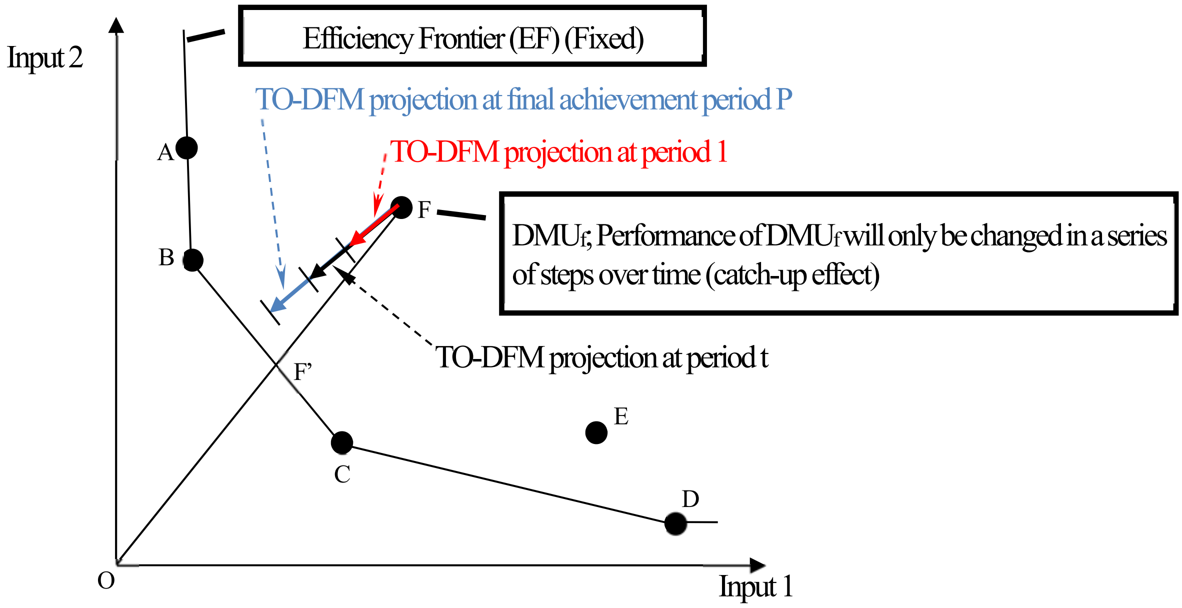


Figure 5 Illustration of TS-TO-DFM model

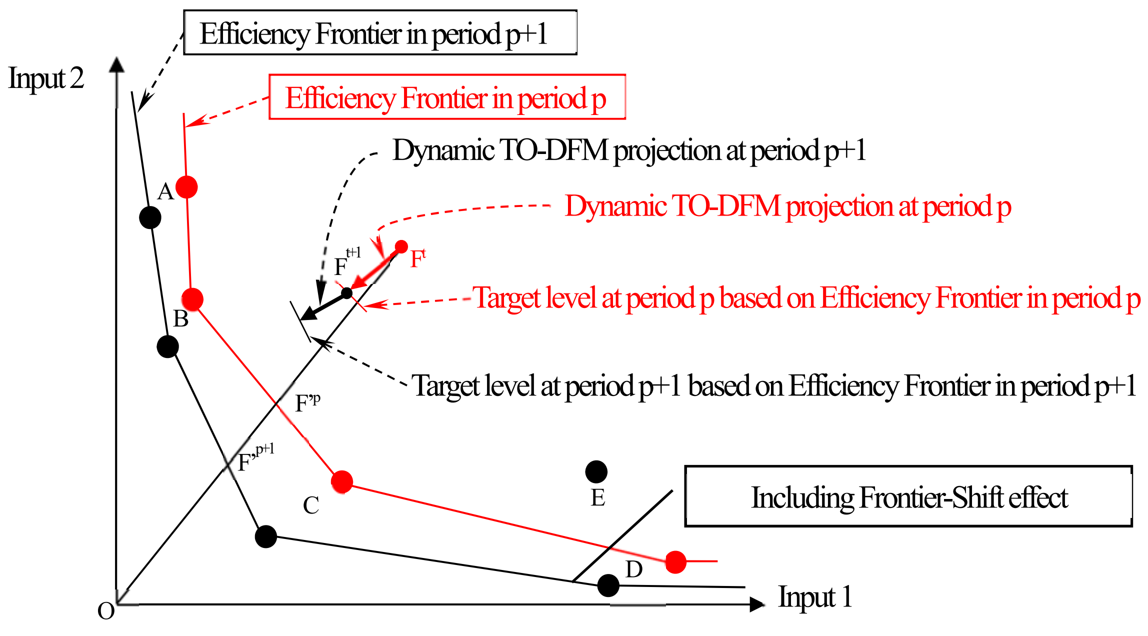


Figure 6 Illustration of Dynamic TO-DFM model

From Figure 5, 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 Figure 5.

In contrast, from Figure 6 we notice that an 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 Figure 6.

4. An evaluation of the economic performance of Japanese cities

4.1 Database and analytical framework

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) to evaluate and compare their broad economic efficiency. The DMUs used in our analysis are listed in Table 1.

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

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; data acquisition from each city's website);

(I2) City budget (Reference: Ministry of Internal Affairs and Communications; source: Statistical Yearbook of Local Government Finance 2007-2013. http://www.soumu.go.jp/iken/zaisei/toukei.html)

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

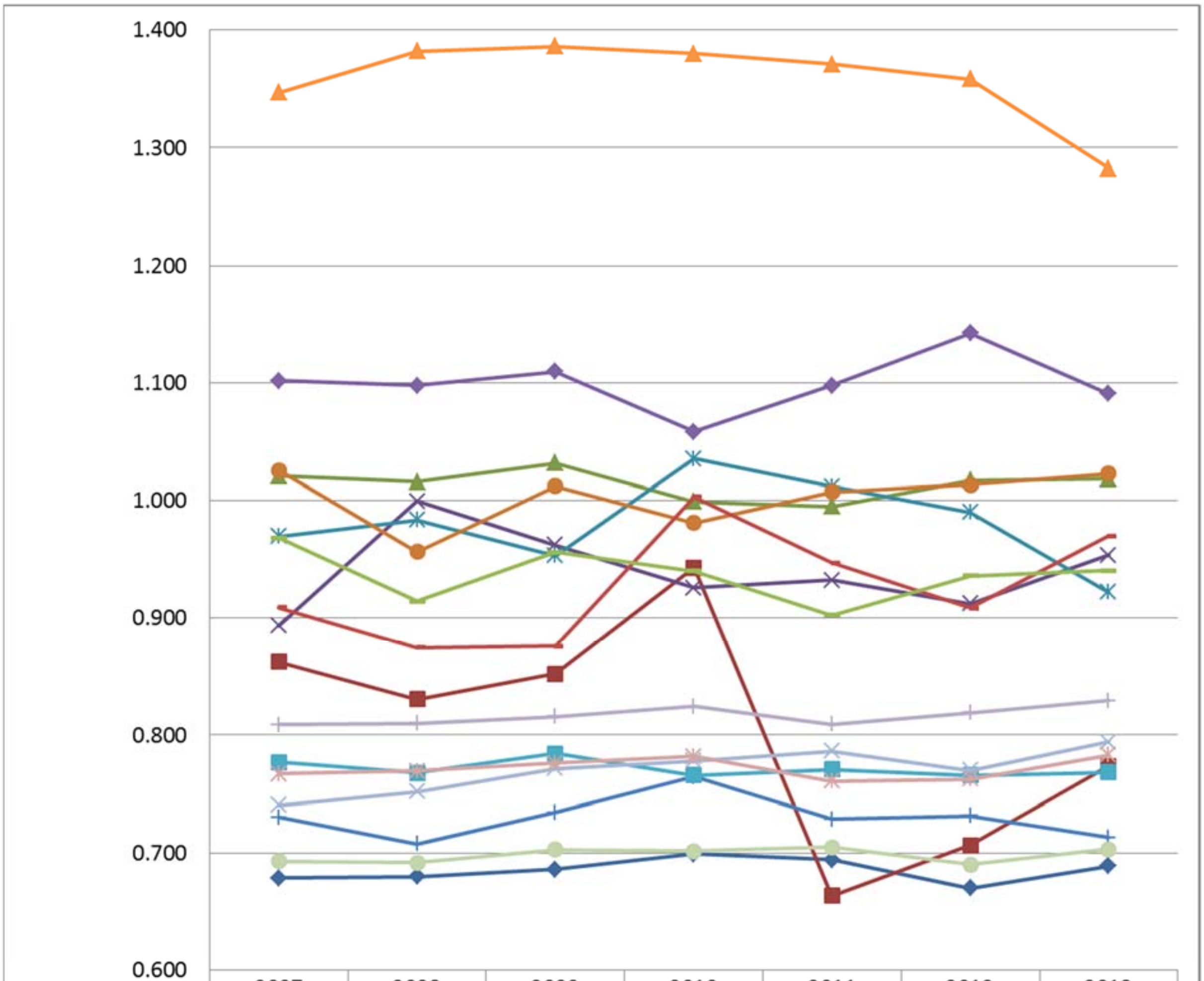
(O1) GDP (Reference: municipal accounts, data acquisition from each city's website);

(O2) Tax revenues (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 Figure 6.

From Figure 6, it can be seen that Osaka, Nagoya, Kawasaki and Saitama in 2013 may be regarded as super-efficient cities. 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 direct influence of the Tohoku 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; it seems 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.



	2007	2008	2009	2010	2011	2012	2013
Sapporo	0.679	0.680	0.686	0.699	0.694	0.670	0.689
Sendai	0.862	0.831	0.852	0.943	0.664	0.707	0.774
Saitama	1.021	1.016	1.032	0.999	0.995	1.017	1.018
Chiba	0.894	0.999	0.962	0.926	0.932	0.912	0.954
Yokohama	0.969	0.983	0.953	1.035	1.012	0.990	0.922
Kawasaki	1.025	0.957	1.012	0.981	1.007	1.014	1.023
Niigata	0.730	0.708	0.734	0.765	0.729	0.731	0.713
Shizuoka	0.909	0.875	0.876	1.003	0.947	0.909	0.970
Hamamatsu	0.968	0.914	0.956	0.940	0.902	0.936	0.941
Nagoya	1.102	1.098	1.109	1.058	1.098	1.142	1.090
Kyoto	0.777	0.768	0.784	0.766	0.771	0.766	0.768
Osaka	1.347	1.382	1.386	1.380	1.371	1.358	1.283
Kobe	0.741	0.752	0.771	0.778	0.786	0.770	0.794
Hiroshima	0.767	0.769	0.776	0.782	0.761	0.763	0.783
Kitakyushu	0.693	0.692	0.703	0.702	0.705	0.690	0.703
Fukuoka	0.809	0.810	0.816	0.824	0.809	0.819	0.829

Figure 7 Efficiency scores for Japanese big cities based on the SE-CCR-I model

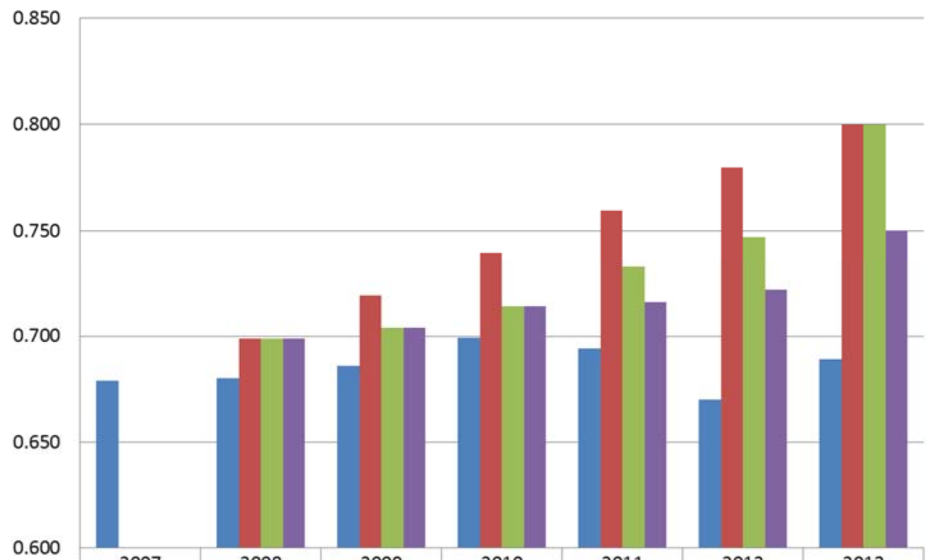
4.3 Efficiency improvement projection based on TS-TO-DFM model and the Dynamic TO-DFM models for Sapporo

Next, the above-mentioned Dynamic TO-DFM model will be 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 Figure 8. The 2007 efficiency value for Sapporo is 0.679, and we set the origin period p = 0 at 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). The final TES for Sapporo 2013 is somewhat arbitrarily set at 0.800. Each TES for each year calculated by the TS-TO-DFM model and the Dynamic TO-DFM model is shown in Figure 8. Especially the TES for each year calculated by the Dynamic TO-DFM model represents a frontier shift effect, as shown in Figure 6. 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 Figure 9 and 10.

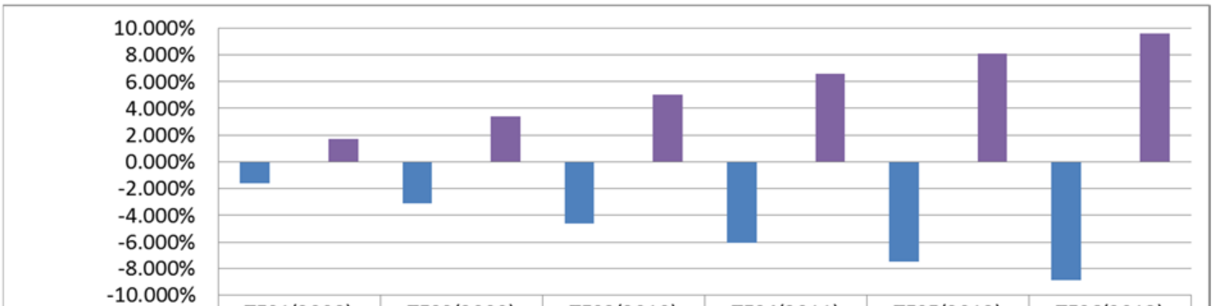
From Figure 9, we notice that the projection results of the TS-TO-DFM model seem to be linearly increasing values in a rather simplistic form year by year.

In contrast, from Figure 10 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 0.800 in 2013. We also notice that the TES from 2011 to 2013 might represent an unrealistic situation, as is does not incorporate an influence of the Tohoku 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 Figure 7. 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 $\mathrm{FTES}^{2013}_{Adjustment}$ set at 0.750, while each target score is set for each year from 2011 to 2013 in Figure 8. The result of this revised Dynamic target TO-DFM model is presented in Figure 11.



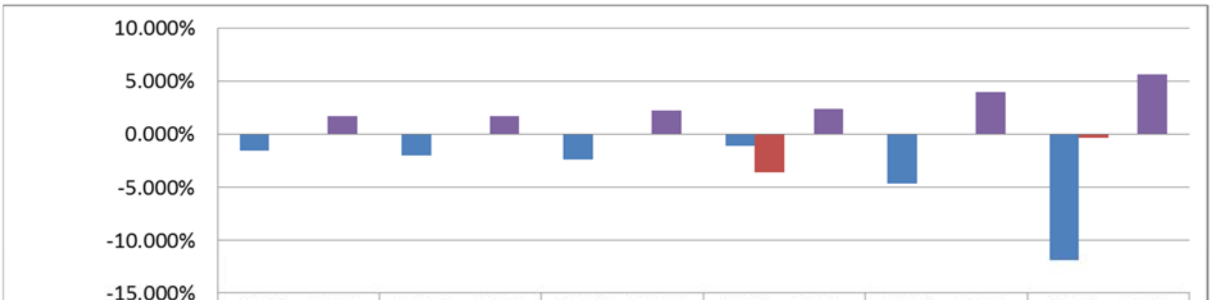
	2007	2008	2009	2010	2011	2012	2013
real efficiency Score	0.679	0.680	0.686	0.699	0.694	0.670	0.689
TES for each year by TS-DFM for 2013		0.699	0.719	0.739	0.760	0.780	0.800
TES for each year by Dynamic-DFM for 2013		0.699	0.704	0.714	0.733	0.747	0.800
TES(revised in 2011) for each year by Dynamic-DFM for 2013		0.699	0.704	0.714	0.716	0.722	0.750

Figure 8 Efficiency score and Target Efficiency Score (TES) for each year in Sapporo



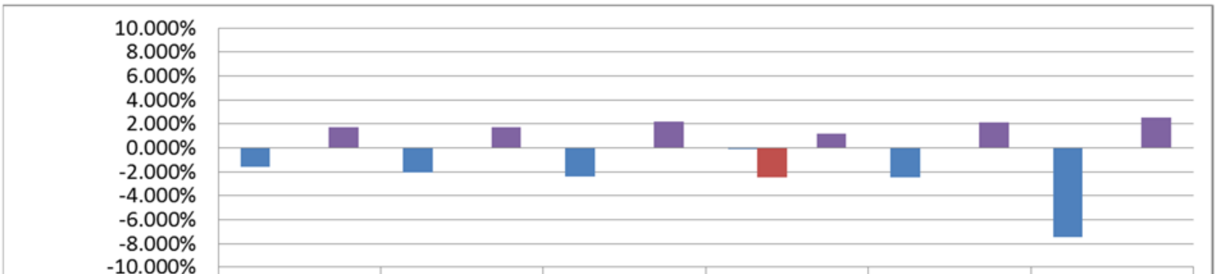
	TES1(2008) =0.699	TES2(2009) =0.719	TES3(2010) =0.739	TES4(2011) =0.760	TES5(2012) =0.780	TES6(2013) =0.800
(I)Budget	-1.585%	-3.124%	-4.619%	-6.072%	-7.485%	-8.860%
(I)Population	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
(O)GDP	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
(O)Tax revenues	1.711%	3.373%	4.988%	6.557%	8.083%	9.567%

Figure 9 Efficiency-improvement projection results based on the TS-TO-DFM model (Sapporo)



	TES for 2008 =0.699	TES for 2009 =0.704	TES for 2010 =0.714	TES for 2011 =0.733	TES for 2012 =0.747	TES for 2013 =0.800
(I)Budget	-1.585%	-2.037%	-2.408%	-1.121%	-4.638%	-11.894%
(I)Population	0.000%	0.000%	0.000%	-3.619%	-0.003%	-0.360%
(O)GDP	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
(O)Tax revenues	1.711%	1.733%	2.196%	2.344%	3.932%	5.619%

Figure 10 Efficiency-improvement projection results based on the Dynamic-TO-DFM model (Sapporo)



	TES for 2008 =0.699	TES for 2009 =0.704	TES for 2010 =0.714	Revised TES for 2011 =0.716	Revised TES for 2012 =0.722	Revised TES for 2013 =0.750
(I)Budget	-1.585%	-2.037%	-2.408%	0.000%	-2.490%	-7.468%
(I)Population	0.000%	0.000%	0.000%	-2.440%	0.000%	0.000%
(O)GDP	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
(O)Tax revenues	1.711%	1.733%	2.196%	1.194%	2.111%	2.504%

Figure 11 Efficiency-improvement projection results based on the revised target Dynamic TO-DFM model (Sapporo)

From Figure 11, it is noteworthy that the Dynamic TO-DFM model shows the characteristics of flexibility and implementability in urban policy programmes.

5. Conclusion

In this paper, we have 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 the relevant indicators. From the above finding, we note that the Dynamic TO-DFM model is able to present a realistic efficiency-improvement plan 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 more realistic efficiency-improvement urban development plan, and may thus provide a meaningful contribution to decision making and planning for efficiency improvement of Japanese big cities.

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Appendix

A1. Outline of DEA and Efficiency Improvement Projection

The standard Charnes et al. (1978) model (abbreviated hereafter as the CCR-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:

$$(FP_k) \quad \max_{v,u} \quad \theta = \frac{\sum_s u_s y_{sk}}{\sum_m v_m x_{mk}}$$

$$\text{s.t.} \quad \frac{\sum_s u_s y_{sj}}{\sum_m v_m x_{mj}} \le 1 \;\; (j = 1,\cdots,J) \qquad \text{(A.1)}$$

$$v_m \ge 0 \,, \; u_s \ge 0 \,,$$

where θ represents an objective variable function (efficiency score); x_{mj} is the volume of input m ($m = 1,\ldots,M$) for DMU$_j$($j = 1,\ldots,J$); y_{sj} is the output s ($s = 1,\ldots,S$) of DMU j; and v_m and u_s are the weights given to input m and output s, respectively. Model (A.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 (A.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 (A.1) is obviously a fractional programming model, which may be solved stepwise by first assigning an arbitrary value to the denominator in (A.1), and then 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 (A.2) and (A.3) as:

$$\hat{x}_k = \theta^* x_k - s^{-*}; \qquad \text{(A.2)}$$

$$\hat{y}_k = y_k + s^{+*} \qquad \text{(A.3)}$$

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 A1).

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 A1 (θ^*=OC'/OC).

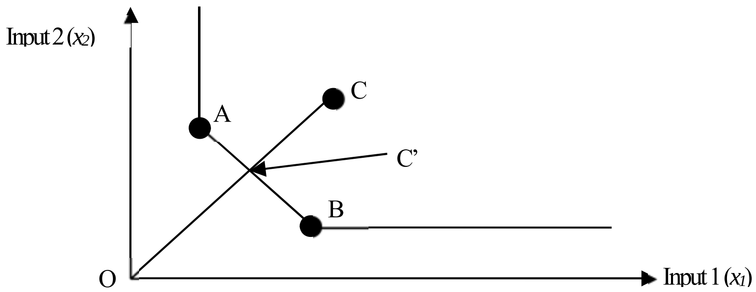

Figure A1 Illustration of original DEA projection in input space

A2. 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 now be written as follows:

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

$$\text{s.t.} \quad \theta x_k = \sum_{j=1,\neq k}^{J} \lambda_j x_j + s^- \tag{A.4}$$

$$y_k = \sum_{j=1,\neq k}^{J} \lambda_j y_j - s^+$$

$$\lambda_j, s^-, s^+ \geq 0,$$

where e is a unit vector (1,...,1), representing a utility factor for all elements.