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The Rat Race Between World Cities

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The Rat Race Between World Cities: In Search of Exceptional Places by Means of Super-Efficient Data Development Analysis

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Abstract

This paper aims to provide a new methodological and empirical contribution to the rising literature on the relative performance and benchmarking of large cities in a competitive world. On the basis of a recent detailed database on many achievement criteria of 35 major cities in the world, it seeks to arrive at a relative performance ranking of these cities by using Data Envelopment Analysis (DEA). A novel element is the use of a new type of 'Super-Efficiency DEA' to identify unambiguously the high performers ('exceptional places') in the group of world cities investigated. This new productivity-based approach is complemented with two new directions in DEA research, viz. a Distance Friction Method and a Context-Dependent method.

Keywords: world cities; city performance; Data Envelopment Analysis

JEL: C8, O1

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1. Exceptional Cities

The structural and worldwide urbanization trend has prompted the emergence of metropolitan areas of an unprecedented scale. Especially in the current globalization age, such areas act as international power stations, with a rich pluriformity of centripetal and centrifugal economic, political and technological forces. Such world cities have a strong global control and command impact, not only because of their sheer size, but more so because of their innovative and creative potential (Glaeser and Kerr 2009, Sassen 1991, Shefer and Frenkel 1998). In this context, the local R&D, knowledge and learning base also plays an important role (Acs et al. 2002, van Geenhuizen and Nijkamp 2011, Kourtit et al. 2011).

World cities are increasingly also involved in fierce competition on global product and service markets, and consequently these metropolitan areas have to create favourable conditions for economic agents, such as: a healthy entrepreneurial climate; a specialized basis of industrial clusters; a diversified economic structure; an ecologically sustainable urban environment; a high-quality research and educational infrastructure; a balanced population structure with sufficient skills; international accessibility through majors hubs etc. (see also Cheshire and Magrini 2009). World cities are essentially involved in a permanent global battle that is concerned with the maximum development and exploitation of agglomeration externalities in international spatial networks.

An interesting question is now how global players and local experts view the potential and performance of these cities. In recent years, various attempts have been made to develop a classification or ranking of world cities based on their actual performance or their perceived success (see e.g. Taylor et al. 2009, Grosveld 2002, Arribas-Bel et al. 2011; Kourtit et al. 2012a, Suzuki et al. 2011). Especially the seminal work of Taylor and associates has gained world-wide recognition. A main challenge in empirical research is the development of a consistent, quantitative data base that is appropriate for a comparative, strategic benchmark analysis.

One of the most detailed databases on world cities can be found in a recent study on the ‘Global Power City Index’ (GPCI) undertaken by the Institute for Urban Strategies (2010). A thorough analysis of various world cities, 35 in total, was made in this study report, including not only the megacities of New York, London, Paris, Tokyo or Beijing but also cities from emerging economies such as Sao Paulo, Mumbai, Kuala Lumpur or Cairo. The GPCI database contains six major clusters of relevant information on these cities. We employ this database for a benchmark analysis of these cities and, therefore, it is discussed in slightly greater detail in the next section.

The basic proposition of the present paper is that a pure ranking of world cities on the basis of their weighted achievement scores does not tell us very much about their economic efficiency, which in the long run will be decisive for their prosperity and sustainability. Therefore, our study aims to provide a more critical analysis of the performance data on these 35 metropolitan areas by using Data Envelopment Analysis (DEA) to position these cities on the basis of their relative performance, i.e. by relating their output to their input. This ratio is much more informative about the actual economic profile of the city concerned. In this study, we also make a new contribution to DEA analysis: namely, 'Super-Efficiency DEA', combined with a 'Distance Friction Minimization' model by introducing a new method for calculating and identifying super-efficient actors (in our case, cities). This methodology will be explained in Section 3. Then, Sections 4 and 5, respectively, present and interpret the various empirical findings for the database described above. Finally, the paper concludes with some suggestions for follow-up research and policy action.

2. Description of the World Cities Database

For a systematic comparison of cities' performance analysis and their urban competitiveness, our empirical approach is based on a unique data set, the 'Global Power City Index' (GPCI), produced by the Institute for Urban Strategies, under the aegis of the Mori Memorial Foundation (2010) in Tokyo for the year 2010.

The GPCI index is used, as a strategic tool, to evaluate and rank the comprehensive power determinants of 35 major cities worldwide, in terms of the strengths and weaknesses of their performance in: creating wealth; enhancing social development; attracting investments; providing an open and attractive urban 'milieu' or climate; offering access to social capital and networks; encouraging integrated sustainability; and harnessing both human and technological resources in productivity and competitiveness at local and global scales. In other words, the aim of these world cities is to maximize urban XXQ (the highest possible urban quality) which may strengthen their foundations for securing socio-economic development and competitive advantage in a global playing field (Nijkamp 2010).

The comprehensive performance scores and rankings of these global cities in the GPCI-data set are based on six main categories, namely: *"Economy"*, *"Research & Development"*, *"Cultural Interaction"*, *"Liveability"*, *"Ecology & Natural Environment"*, and *"Accessibility"*. Each of these main indicators was subdivided into relevant and measurable sub-indicators, so that finally a consistent and tested database on 69 sub-indicators for 35 world cities was created. Thus, we have a complete, extensive and quantitative database for a great variety of relevant urban (sub-) indicators for all world cities under consideration.

Next, a set of five worldwide types of actors was identified: managers, researchers, artists, visitors, and residents. These people were asked to score the importance of each of these indicators, so that a weighted average importance score for each city could be calculated. All details can be found in the above-mentioned GPCI-2010 report. See Annex A in this paper for more details of the ranking results of these cities as presented in the above mentioned study (more details can also be found in Kourtit et al. 2012b). Figure 1 provides a concise analytical presentation of the main categories of performance indicators derived from the GPCI report.

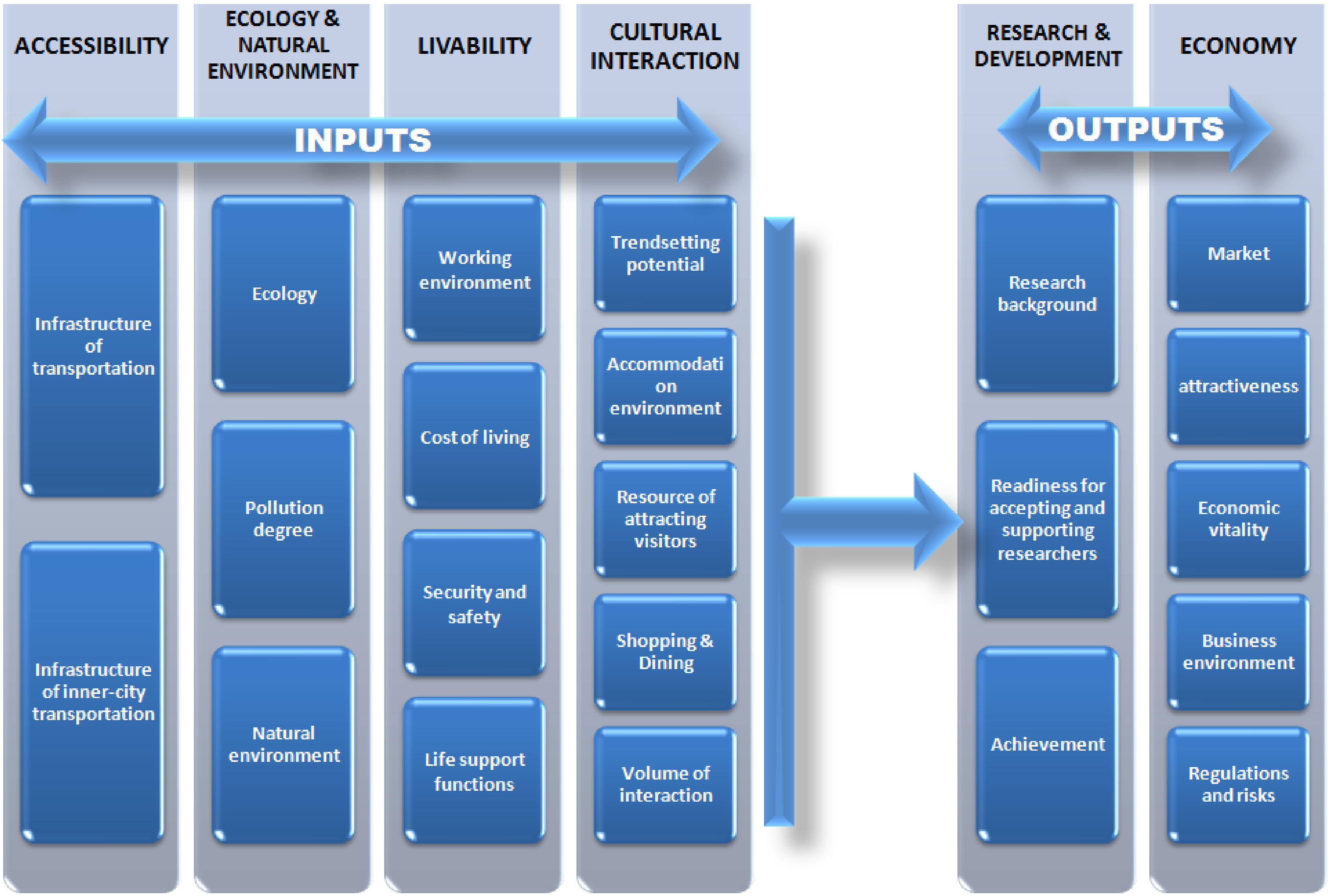

Figure 1. An overview of the main categories of performance indicators used in GPCI-2010.

The GPCI-2010 database was collected systematically for all relevant cities in the sample. It was also carefully checked by both local experts and independent scientists, so that its reliability may be judged as satisfactory. Cleary, the sample of 35 World Cities may be extended in the future, but for our analytical purposes it meets our demands.

This operational framework of empirical information is used in our DEA analysis in order to explore and represent in a comparative sense the super-efficiency performance of these global cities in terms of urban input (or resource) and output indicators and outputs regarding their economic achievement.

3. Data Envelopment Analysis (DEA): New Roads

3.1 The CCR model

In this section, we will outline the various steps of our DEA experiment, starting from a standard DEA tool and proceeded towards a Super-Efficient DEA, while using two additional techniques, viz. a Distance Friction Minimization (DFM) and a (Stepwise) Context-Dependent (CD) method. The standard Charnes et al. (1978) model (abbreviated hereafter as the CCR-input or CCR-I model) for a given Decision-Making Unit DMU$_j$ $(j=1,\cdots,J)$ to be evaluated in any trial o (where o ranges over 1, 2 …, J) may be represented as the following fractional programming (FP_o) problem:

$$(FP_o) \qquad \max_{v,u} \quad \theta = \frac{\sum_s u_s y_{so}}{\sum_m v_m x_{mo}}$$

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

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

where θ represents an objective variable function (efficiency score); x_{mj} is the volume of input m (m=1,…, M) for DMU j (j=1,…,J); y_{sj} is the output s (s=1,…,S) of DMU j; and v_m and u_s are the weights given to input m and output s, respectively. Model (1) is usually called an input-oriented CCR model, while its reciprocal (i.e. an interchange of the numerator and denominator in objective function (1), with a specification as a minimization 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 then maximizing the numerator. But it is preferable to transform (1) into a linear programming model, as the CCR model (1) can be shown to have the following equivalent linear programming (LP_o) specification for any DMU $_j$:

$$
\begin{aligned}
(LP_o) \quad & \max_{v,u} \quad \theta = \sum_s u_s y_{so} \\
\text{s.t.} \quad & \sum_m v_m x_{mo} = 1 \\
& -\sum_m v_m x_{mj} + \sum_s u_s y_{sj} \le 0 \\
& v_m \ge 0\,,\; u_s \ge 0\,.
\end{aligned}
\tag{2}
$$

The dual problem of (2), DLP_o, can be expressed by means of a real variable θ, using the following vector notation:

$$
\begin{aligned}
(DLP_o) \quad & \min_{\theta,\lambda} \quad \theta \\
\text{s.t.} \quad & \theta x_o - X\lambda \ge 0 \\
& Y\lambda \ge y_o \\
& \lambda \ge 0\,,
\end{aligned}
\tag{3}
$$

where the transposed (T) presentation $\lambda = \left(\lambda_1, \quad \cdots \quad \lambda_J\right)^T$ is a non-negative vector (corresponding to the presence of slacks for each DMU), X an ($M\times J$) input matrix, and Y an ($S\times J$) input matrix.

We can now define the input excesses $s^- \in R^m$ and the output shortfalls $s^+ \in R^s$, and identify them as 'slack' vectors as follows:

$$s^- = \theta x_o - X\lambda\,; \tag{4}$$

$$s^+ = Y\lambda - y_o\,. \tag{5}$$

These equations indicate that the efficiency of (x_o, y_o) for DMU$_o$ can be improved if the input values are reduced radially by the ratio θ^*, and the input excesses s^{-*} are eliminated (see Figure 2). The original DEA models presented in the literature have thus far only focused on a uniform input reduction or a uniform output increase in the efficiency-improvement projections, as shown in Figure 2 (θ^*=OC'/OC).

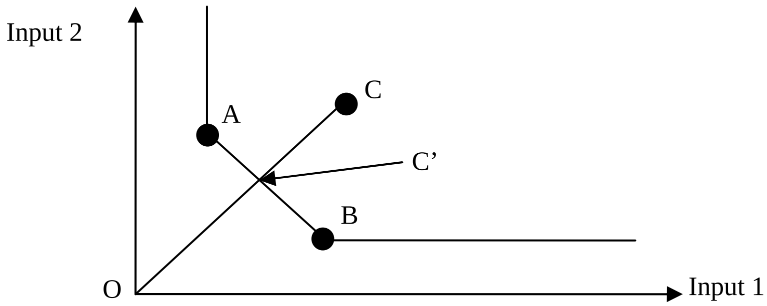

Figure 2. Illustration of original DEA projection in input space

We also observe that the maximum efficiency score to be achieved by efficient DMUs based on the CCR model is 1. In practice, this often means that the CCR model usually computes more than one high-ranking DMU. And that prompts the question whether out of the group of high-ranking DMUs the highest-ranking (super-efficient) DMU can be identified. This will be discussed in subsection 3.2.

3.2 The Super-Efficiency model

The unsatisfactory identification of efficient firms in a standard DEA model – where all efficient firms get the score 1 – has led to focused research to discriminate between efficient DMUs, in order to arrive at a ranking – or even numerical rating – of these efficient firms, without affecting the results for the non-efficiency. In particular, Andersen and Petersen (1993) developed a radial Super-Efficiency model, while later on Tone (2002, 2003) 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 firm, by designing and measuring a score for its 'degree of influence' if this efficient firm 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). Thus, for each individual firm a new distance result is obtained, which leads to a new ranking – even a rating – of all original efficient firms.

The main problem in Super-Efficiency DEA is how to define the distance between an efficient DMU and the production possibility set that emerges after the elimination of one single efficient DMU. In the literature, the SBM (see Tone, 2002, 2003) has been advocated. And this method will also be applied in our empirical investigation.[1]

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[1] In the meantime, the above mentioned literature has also mentioned some more refinements of the SMB approach, such as the Super-SBM-I-C (the super-efficiency SBM method with DEA input-orientation under constant returns to scale), the Super-SBM-I-V (under variable returns to scale), the Super SBM-O-CC (with output orientation under

Anderson and Petersen (1993) have developed the Super-Efficiency 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_o 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_o – 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. The super-efficiency model may be suitable to find for our comparative data base on big cities in the world the set of highest performing smart cities. These can be ranked in descending order and are coined 'Exceptional World Cities' or 'Exceptional Places'.

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

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

$$\text{s.t.} \quad \theta x_o = \sum_{j=1,\neq o}^{J} \lambda_j x_j + s^- \tag{6}$$

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

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

where e is a unit vector (1,...,1), representing a utility factor for all elements. This model will be used in our search for 'Exceptional Places' from which an ambiguous ranking will emerge.

3.3 A new Super-Efficiency DEA based on a Distance Friction Minimization (DFM)

3.3.1 Outline of the Distance Friction Minimization (DFM) approach

As mentioned, the efficiency improvement solution in the original CCR-input model requires that the input values are reduced radially by a uniform ratio θ^* (θ^*=OD'/OD in Figure 2). The (v^*, u^*) values obtained as an optimal solution for formula (1) result in a set of optimal weights for DMU_o; (v^*, u^*) is the set of most favourable weights for DMU_o, in the sense of maximizing the ratio scale. v_m^* is the optimal weight for the 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 the output item s. These values show not only which items contribute to the performance of DMU_o, but also to what extent they do so. In other words, it is possible to calculate the distance frictions (or alternatively, the potential increases) in improvement projections. Suzuki et al. (2010) used the optimal weights u_s^* and v_m^* from (1) as the basis for the efficiency improvement projection model. A visual presentation of this approach is given in Figures 3 and 4.

constant returns to scale), the super-SBM-O-V (under variable returns to scale), and even the Super-SBM-GRS (under general returns to scale) .

In this approach, a generalized distance friction is employed to assist a DMU to improve its efficiency by a movement towards the efficiency frontier surface. The direction of efficiency improvement depends, of course, on the input/output data characteristics of the DMU. It seems appropriate to define the projection functions for the minimization of distance friction by using a Euclidean distance in weighted spaces. This forms the key of the DFM (Distance Friction Minimization) model. 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 may address both input reduction and output increase. We will not provide a detailed description of the various steps involved, but details can be found in Suzuki et al. (2010).

By means of this DFM model, 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 5).

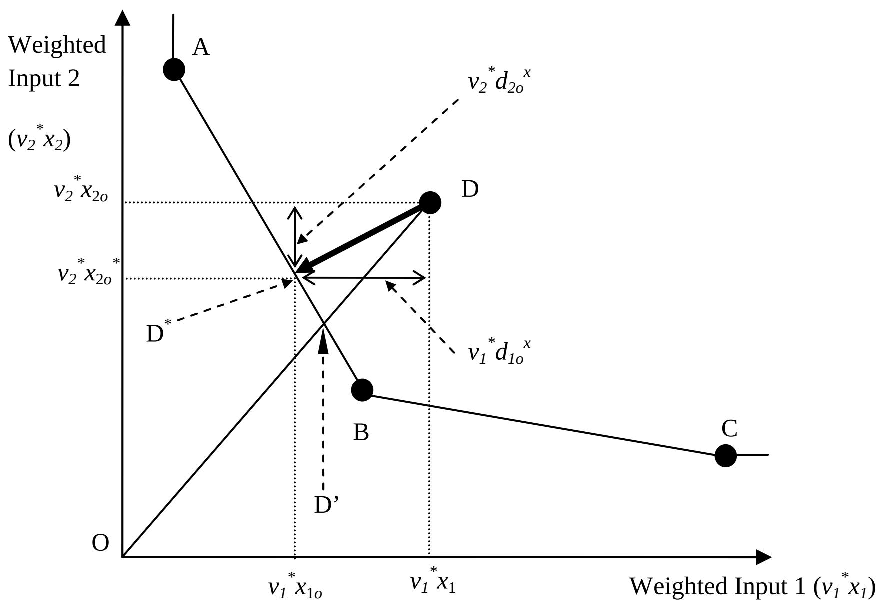

Figure 3. Illustration of the DFM approach (Input- $v_i^* x_i$ space)

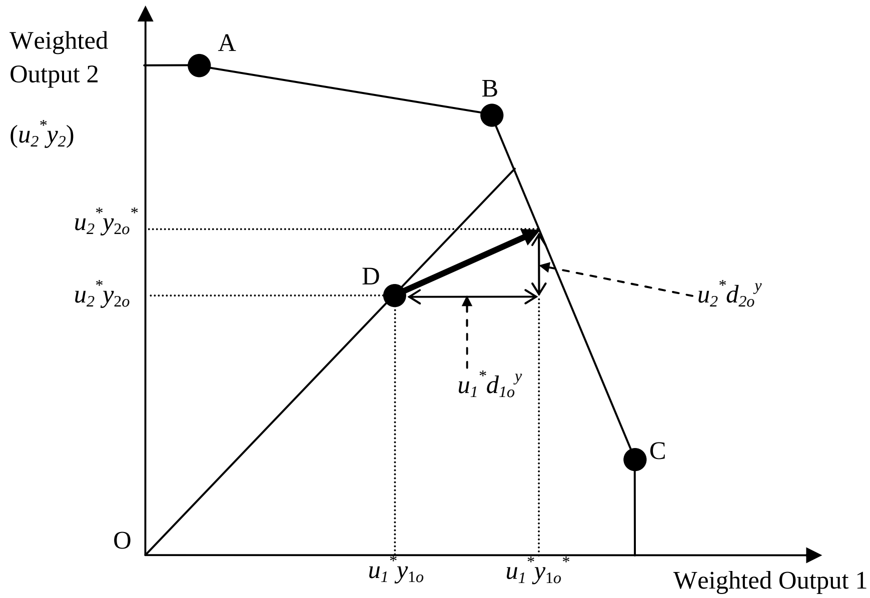

Figure 4. Illustration of the DFM approach (Output - $u_r^* y_r$ space)

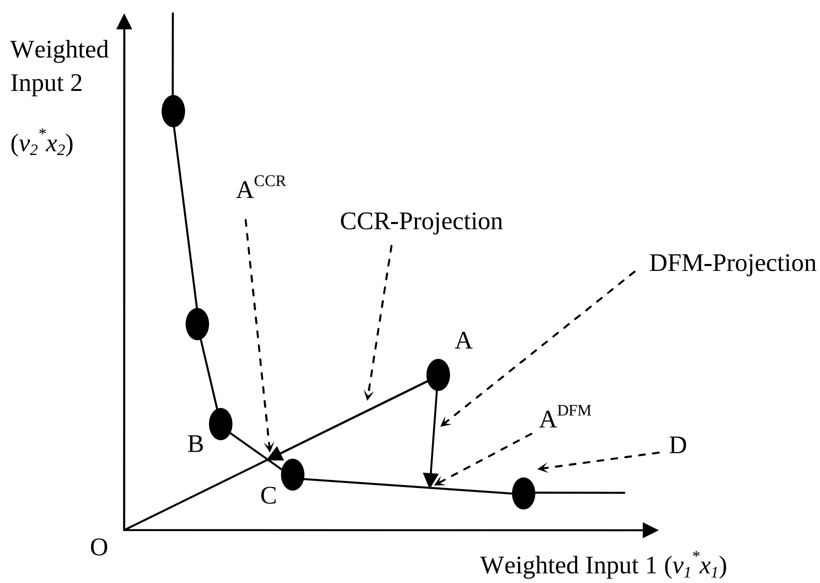

Figure 5. Degree of improvement of the DFM and the CCR projection in weighted input space

3.3.2 A proposal for a Super-Efficiency DFM model

We now design a Super-Efficiency DFM model that is integrated with a Super-Efficiency DEA model.

In a normal DFM model, the (v^*, u^*) values obtained as an optimal solution for formula (1) result in a set of optimal weights for DMU_o. Our new Super-Efficiency DFM model (hereafter SE-DFM) is now based on the idea that these optimal values result from the application of the

Super-Efficiency model. The advantage of the SE-DFM model is that it yields an unambiguous and measurable outcome in a ranking of efficient DMUs, i.e. this new integrated model can be suitable to find the highest performing DMUs, while retaining all the advantages of the DFM model.

3.4 A Stepwise SE-DFM model in DEA

3.4.1 Outline of a Context-Dependent model

The Context-Dependent (hereafter CD) model can generate efficient frontiers in successive stages (levels), and can yield a stepwise level-by-level improvement projection (for details, see Seiford and Zhu, 2003). A concise formulation of the CD model follows now.

Let $J^l = \{DMU_j, j = 1, \cdots, J\}$ be the set of all J DMUs. We interactively define $J^{l+1} = J^l - E^l$, where $E^l = \{DMU_k \in J^l \,|\, \theta^*(l,k)\} = 1$ and $\theta^*(l,k)$ is the optimal value by using formula (1) (see Figure 6). When l = 1, the model becomes the original CCR model, while the DMUs in set E1 define the first-level efficient frontier. When l = 2, it gives the second-level efficient frontier after the exclusion of the first-level efficient DMUs, and so on. In this manner, we identify several levels of efficient frontiers. We call El the lth-level efficient frontier. The following algorithm accomplishes the identification of these efficient frontiers.

Step 1: Set l = 1. Evaluate the entire set of DMUs, J1. We then obtain the first-level efficient DMUs for set E1 (the first-level efficient frontier).

Step 2: Exclude the efficient DMUs from future DEA runs, i.e. $J^{l+1} = J^l - E^l$ (If $J^{l+1} = \phi$, then stop.)

Step 3: Evaluate the new subset of “inefficient” DMUs. We then obtain a new set of efficient DMUs E^{l+1} (the new efficient frontier).

Step 4: Let $l = l$ + 1. Go to step 2.

Stopping rule: $J^{l+1} = \phi$, the algorithm is terminated.

A visual presentation of the CD model is given in Figure 6.

3.4.2 An operational Stepwise SE-DFM Model

Any efficiency-improving projection model which includes the standard CCR projection supplemented with the SE-DFM projection is always directed towards achieving “full efficiency”. This strict condition may not always be easy to achieve in reality. Therefore, in this section we will integrate the CD model with the SE-DFM approach; this will be called the “Stepwise SE-DFM” model. It can yield a stepwise efficiency-improving projection that depends on l-level efficient frontiers (l-level DFM projection), as shown in Figure 7.

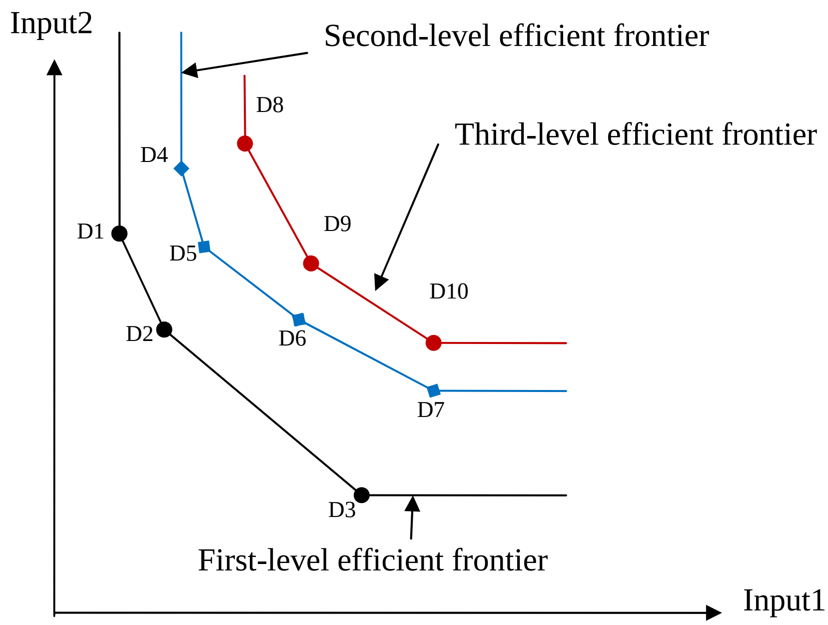

Figure 6. Illustration of the CD model

For example, a second-level DFM projection for DMU10 (D10) aims to position DMU10 on a second-level efficient frontier. In addition, a first-level DFM projection is just equal to an SE-DFM projection. We observe here that the second-level DFM projection is easier to achieve than a first-level DFM projection. A Stepwise SE-DFM model can yield a more practical and realistic efficiency improving projection than a CCR projection or a SE-DFM projection.

The advantage of the Stepwise SE-DFM model is that it also yields an outcome on a *l*-level efficient frontier that is as close as possible to the DMU's input and output profile, which means that the Stepwise SE-DFM projection can compute more effective solutions than the CD projection model (see Figure 7). This set of new DEA applications will now be applied to the GPCI database on world cities described in Section 2.

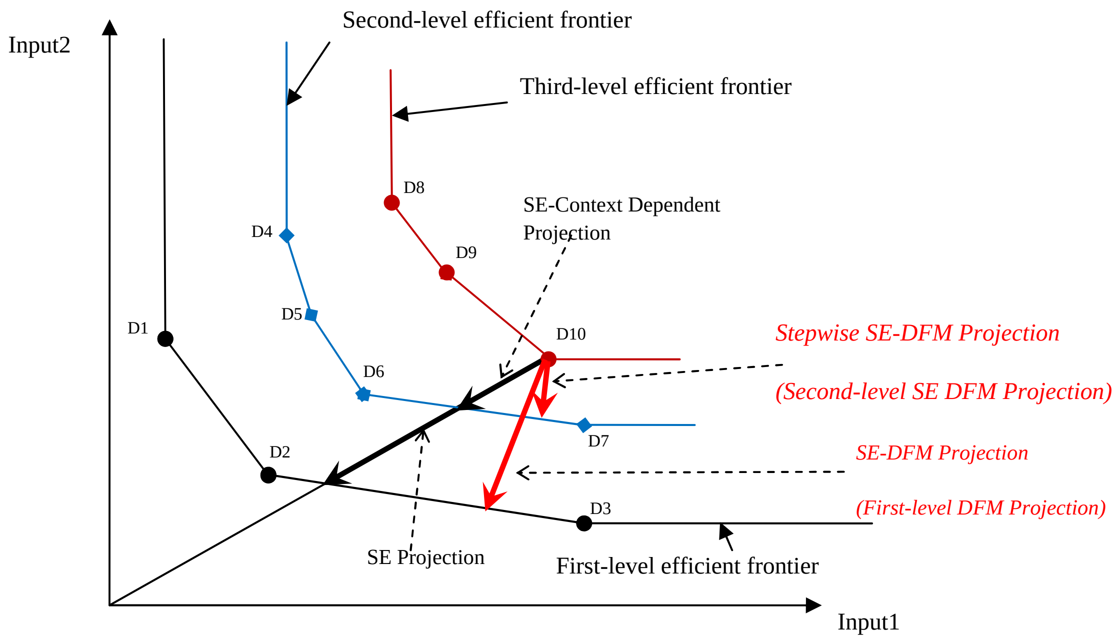

Figure 7. Illustration of the Stepwise DFM model

4. In Search of Exceptional World Cities

In our empirical application we will use the GPCI-2010 database-2010. But rather than seeking to achieve a ranking of cities based on a comprehensive set of indicators, we aim to look at the efficiency (or productivity) of these cities, by investigating more carefully the ratio between multi-attribute outputs and multi-attribute inputs. To that end, DEA is an appropriate tool.

In our application, we will first apply the CCR model and the Super-efficiency model in our search for exceptional world cities based on a super-efficiency DEA. In addition, we will apply the CD model based on the super-efficiency concept; in this way, the cities in our sample can be categorized according to efficiency-levels based on successive levels of efficient frontiers.

4.1 Efficiency scores for super-efficiency and CCR-I

The efficiency evaluation results for the 35 world cities based on the CCR model and the Super-efficiency model using 4 inputs ("Cultural Interaction", "Liveability", "Ecology & Natural Environment", "Accessibility") and 2 outputs ("Economy", "Research & Development") are given in Figure 8. The standard CCR model assigns an equal efficiency to 9 world cities, viz. New York, Boston, Genève, Moscow, Beijing, Hong Kong, Tokyo, Los Angeles and Fukuoka, so that it is not possible to discriminate among these cities. However, by applying a Super-

Efficient DEA model a clear difference in performance of these 9 cities can be observed (see Figure 8).

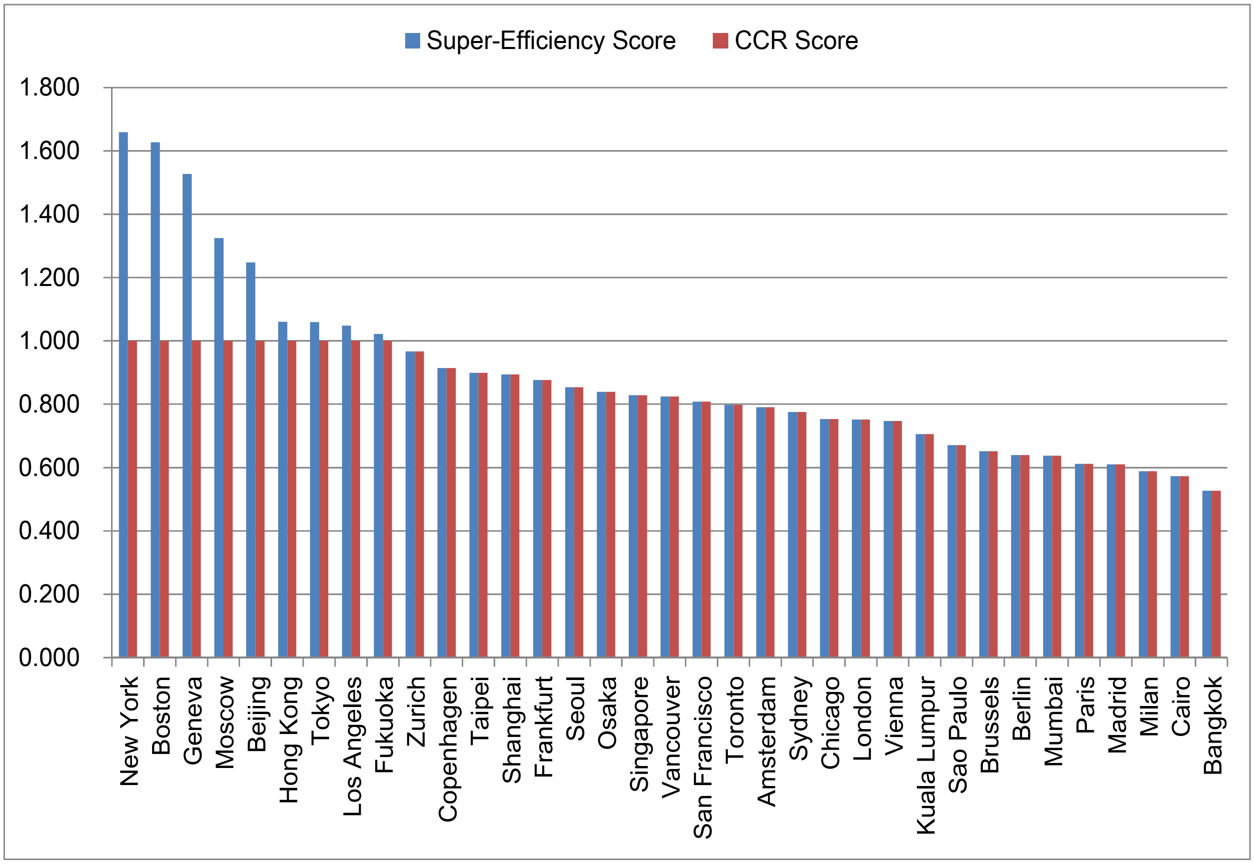

Figure 8. Efficiency score based on the CCR model and the Super-Efficiency model

In Figure 8, the rankings of the super-efficiency values for 9 of the 35 world cities (i.e. New York, 1.659; Boston, 1.628; Geneva, 1.527; Moscow, 1.325; Beijing, 1.248; Hong Kong, 1.060; Tokyo, 1.059; Los Angeles, 1.048; and Fukuoka, 1.022) were identified on the basis of their high Super-Efficiency score. It is noteworthy that in our analysis "New York" is *the* 'Exceptional World City' based on the Super-Efficiency model. This is an unambiguous result that originates from the advantages of the design of the Super-Efficiency model.

It should be added that these results differ quite considerably from those achieved in the original GPCI-2010 report (see Annex). The reason is that our productivity-based analysis allows non-megacities (such as Boston or Geneva) to achieve a favourable efficiency outcome, in which size and agglomeration effects are combined with smart management of the urban area concerned. Nevertheless, metropolitan areas like New York or Tokyo have managed to maintain their high ranking in our efficiency analysis. Clearly, there are economies of scale for world cities, but some medium-sized world cities appear to perform exceptionally well.

4.2 Efficiency scores and categorization based on CD-Super-Efficiency

The detailed efficiency evaluation results for the 35 world cities based on the CD-Super-Efficiency model with the six performance categories E1-E6 are given in Figure 9.

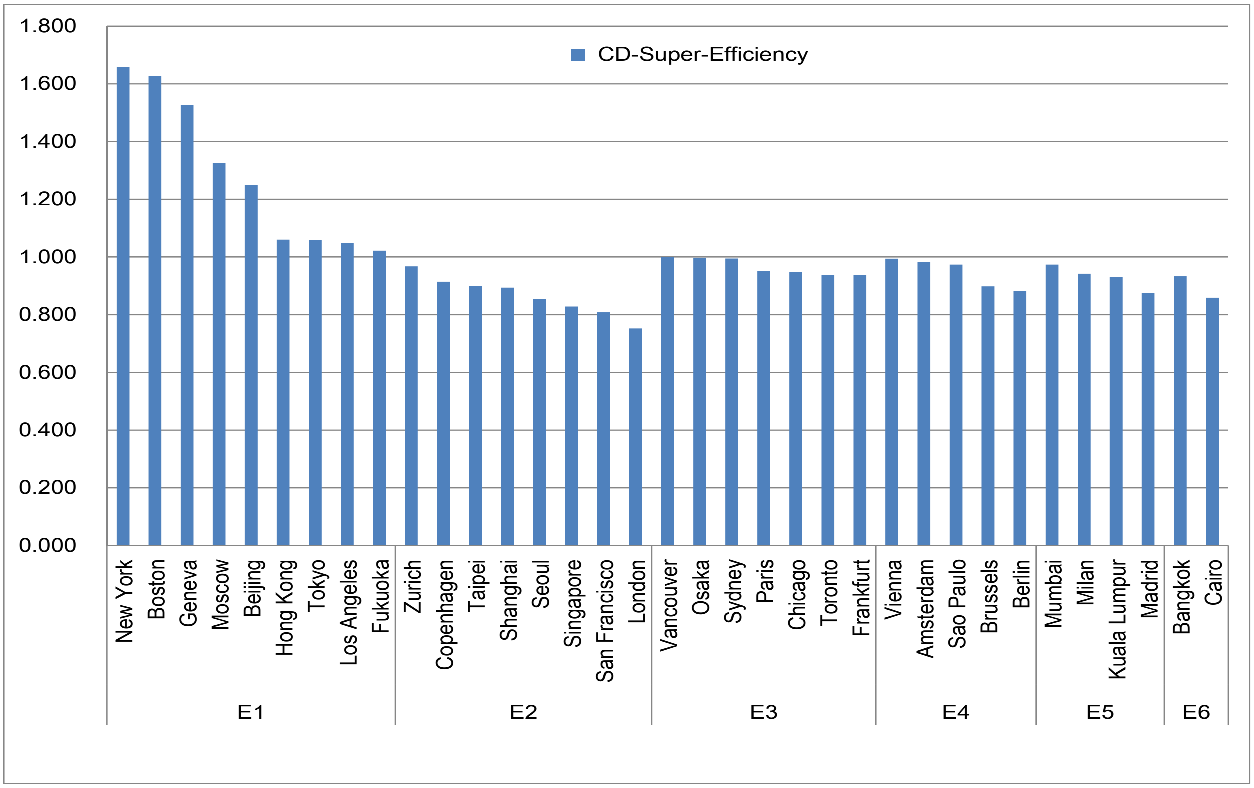

Figure 9. Efficiency scores and categorizations based on CD-Super-Efficiency

In Figure 9, the DMUs in set E1 (New York, Boston, Geneva, Moscow, Beijing, Hong Kong, Tokyo, Los Angeles, and Fukuoka) represent the cities with the highest efficiency (these cities correspond to D1, D2 and D3 in Figure 6, which define the first-level efficient frontier group). These nine are identified on the basis of the Super-Efficient DMU concept.

The eight DMUs in set E2 (Zurich, Copenhagen, Taipei, Shanghai, Seoul, Singapore, San Francisco, and London) are the second-tier efficient cities (these cities correspond to D4, D5, D6 and D7 in Figure 6, which define the second-level efficient frontier group), after the exclusion of the first-level efficient cities. The seven DMUs in set E3 (Vancouver, Osaka, Sydney, Paris, Chicago, Toronto, and Frankfurt) relate to the third-level efficient cities, after the exclusion of the second-level efficient cities. Next, the five DMUs in set E4 (Vienna, Amsterdam, Sao Paulo, Brussels, and Berlin) are fourth-level efficient cities, while the DMUs in set E5 (Mumbai, Milan, Kuala Lumpur, and Madrid) and the DMUs in set E6 (Bangkok and Cairo) represent the fifthlevel and sixth-level efficient frontier, respectively.

On the basis of these more differentiated performance categories, we will compute in a quantitative sense an efficiency-improvement projection for the nearest upper-level efficient frontier for inefficient cities in the next section.

5. Efficiency Improvement Projection for Inefficient Cities

5.1 Direct efficiency-improving projection based on SE and SE-DFM models

The direct efficiency improvement projection results based on the SE and the SE-DFM model for inefficient cities are presented in Tables 1a and 1b.

Table 1a. Direct efficiency improvement projection of the SE and SE-DFM model

DMU	Score	SE model Score(θ**)		SE-DFM model Score(θ**)	
I/O	Data	Difference	%	Difference $d_{io}^{x*}-s^{-**}$ $d_{ro}^{y*}+s^{+**}$	%
London	0.752	1.000		1.000	
(I)Cultural Exchange	60.6	-18.5	-30.6%	0.0	0.0%
(I)Livability	44.3	-11.0	-24.8%	0.0	0.0%
(I)Environment	57.8	-14.3	-24.8%	-13.0	-22.5%
(I)Accessibility	56.0	-15.8	-28.2%	0.0	0.0%
(O)Economy	50.5	0.0	0.0%	7.2	14.2%
(O)R&D	44.1	15.4	34.9%	0.0	0.0%
Paris	0.612	1.000		1.000	
(I)Cultural Exchange	51.3	-20.2	-39.4%	0.0	0.0%
(I)Livability	55.6	-23.9	-42.9%	0.0	0.0%
(I)Environment	56.2	-21.8	-38.8%	-18.5	-32.9%
(I)Accessibility	57.9	-22.4	-38.8%	0.0	0.0%
(O)Economy	42.9	0.0	0.0%	12.5	29.1%
(O)R&D	40.3	0.0	0.0%	0.0	0.0%
Singapore	0.829	1.000		1.000	
(I)Cultural Exchange	31.0	-5.3	-17.1%	0.0	0.0%
(I)Livability	38.6	-6.6	-17.1%	-6.3	-16.3%
(I)Environment	59.0	-10.1	-17.1%	0.0	0.0%
(I)Accessibility	42.1	-7.2	-17.1%	0.0	0.0%
(O)Economy	43.0	0.0	0.0%	4.0	9.4%
(O)R&D	29.7	3.5	12.0%	0.0	0.0%
Berlin	0.639	1.000		1.000	
(I)Cultural Exchange	28.2	-14.3	-50.7%	0.0	0.0%
(I)Livability	48.7	-17.6	-36.1%	0.0	0.0%
(I)Environment	66.8	-24.5	-36.7%	0.0	0.0%
(I)Accessibility	32.6	-11.8	-36.1%	-11.0	-33.9%
(O)Economy	33.8	0.0	0.0%	7.8	23.0%
(O)R&D	22.7	0.0	0.0%	0.0	0.0%
Amsterdam	0.791	1.000		1.000	
(I)Cultural Exchange	17.9	-3.7	-20.9%	0.0	0.0%
(I)Livability	48.2	-10.1	-20.9%	-9.2	-19.0%
(I)Environment	65.3	-13.7	-20.9%	0.0	0.0%
(I)Accessibility	41.0	-10.8	-26.4%	0.0	0.0%
(O)Economy	40.1	0.0	0.0%	4.7	11.7%
(O)R&D	18.5	3.1	17.0%	0.0	0.0%
Seoul	0.854	1.000		1.000	
(I)Cultural Exchange	20.9	-3.0	-14.6%	0.0	0.0%
(I)Livability	38.8	-5.7	-14.6%	-4.5	-11.6%
(I)Environment	55.8	-10.9	-19.5%	0.0	0.0%
(I)Accessibility	36.1	-6.8	-19.0%	0.0	0.0%
(O)Economy	36.4	0.0	0.0%	3.8	10.5%
(O)R&D	40.2	0.0	0.0%	0.0	0.0%
Sydney	0.776	1.000		1.000	
(I)Cultural Exchange	23.2	-7.9	-34.0%	0.0	0.0%
(I)Livability	45.2	-10.1	-22.4%	0.0	0.0%
(I)Environment	60.4	-14.1	-23.4%	0.0	0.0%
(I)Accessibility	29.7	-6.7	-22.4%	-5.8	-19.6%
(O)Economy	37.8	0.0	0.0%	5.0	13.1%
(O)R&D	22.2	0.0	0.0%	0.0	0.0%

DMU	Score	SE model Score(θ**)		SE-DFM model Score(θ**)	
I/O	Data	Difference	%	Difference $d_{io}^{x*}-s^{-**}$ $d_{ro}^{y*}+s^{+**}$	%
Vienna	0.747	1.000		1.000	
(I)Cultural Exchange	24.9	-11.7	-47.2%	0.0	0.0%
(I)Livability	47.5	-12.0	-25.3%	0.0	0.0%
(I)Environment	64.3	-18.9	-29.3%	0.0	0.0%
(I)Accessibility	28.7	-7.3	-25.3%	-6.7	-23.1%
(O)Economy	36.7	0.0	0.0%	5.5	14.9%
(O)R&D	15.6	0.0	0.0%	0.0	0.0%
Zurich	0.967	1.000		1.000	
(I)Cultural Exchange	8.0	-0.3	-3.3%	0.0	0.0%
(I)Livability	45.7	-1.5	-3.3%	-0.9	-1.9%
(I)Environment	71.4	-5.5	-7.7%	-4.3	-6.1%
(I)Accessibility	29.6	-6.3	-21.3%	-5.6	-18.8%
(O)Economy	41.3	0.0	0.0%	0.7	1.8%
(O)R&D	19.2	0.0	0.0%	0.0	0.0%
Frankfurt	0.876	1.000		1.000	
(I)Cultural Exchange	10.5	-1.3	-12.4%	0.0	0.0%
(I)Livability	45.2	-5.6	-12.4%	-4.5	-9.9%
(I)Environment	66.5	-8.2	-12.4%	0.0	0.0%
(I)Accessibility	38.5	-14.3	-37.3%	0.0	0.0%
(O)Economy	38.5	0.0	0.0%	2.5	6.6%
(O)R&D	13.8	4.5	32.8%	0.0	0.0%
Madrid	0.610	1.000		1.000	
(I)Cultural Exchange	21.4	-8.4	-39.0%	0.0	0.0%
(I)Livability	48.6	-18.9	-39.0%	-20.3	-41.7%
(I)Environment	60.6	-23.6	-39.0%	0.0	0.0%
(I)Accessibility	35.4	-13.8	-39.0%	0.0	0.0%
(O)Economy	32.1	0.0	0.0%	7.8	24.2%
(O)R&D	10.9	2.8	25.8%	0.0	0.0%
Vancouver	0.825	1.000		1.000	
(I)Cultural Exchange	12.4	-2.2	-17.5%	0.0	0.0%
(I)Livability	60.7	-25.8	-42.6%	-22.4	-36.9%
(I)Environment	56.4	-9.9	-17.5%	-10.1	-17.9%
(I)Accessibility	25.9	-4.5	-17.5%	0.0	0.0%
(O)Economy	34.6	0.0	0.0%	3.7	10.8%
(O)R&D	17.8	0.0	0.0%	0.0	0.0%
Copenhagen	0.914	1.000		1.000	
(I)Cultural Exchange	11.2	-1.0	-8.6%	0.0	0.0%
(I)Livability	46.7	-4.0	-8.6%	-3.1	-6.7%
(I)Environment	62.7	-5.4	-8.6%	0.0	0.0%
(I)Accessibility	31.3	-3.4	-11.0%	-3.2	-10.2%
(O)Economy	41.1	0.0	0.0%	1.8	4.5%
(O)R&D	13.5	6.0	44.3%	7.4	54.8%
Osaka	0.839	1.000		1.000	
(I)Cultural Exchange	12.9	-2.1	-16.1%	0.0	0.0%
(I)Livability	51.6	-16.9	-32.7%	-13.5	-26.1%
(I)Environment	52.8	-8.5	-16.1%	-9.4	-17.8%
(I)Accessibility	30.5	-4.9	-16.1%	0.0	0.0%
(O)Economy	34.0	0.0	0.0%	3.8	11.2%
(O)R&D	24.1	0.0	0.0%	0.0	0.0%

Legend: I = Input ; O = Output

Table 1b. Direct efficiency improvement projection of the SE and SE-DFM model

DMU	Score	SE model		SE-DFM model	
		Score(θ**)		Score(θ**)	
I/O	Data	Difference	%	Difference $d_{io}^{x*}-s^{-**}$ $d_{ro}^{y*}+s^{+**}$	%
Brussels	0.652	1.000		1.000	
(I)Cultural Exchange	21.4	-7.4	-34.8%	0.0	0.0%
(I)Livability	46.9	-16.3	-34.8%	-17.8	-37.8%
(I)Environment	52.7	-18.3	-34.8%	0.0	0.0%
(I)Accessibility	34.4	-12.0	-34.8%	0.0	0.0%
(O)Economy	32.8	0.0	0.0%	7.0	21.4%
(O)R&D	14.7	0.0	0.0%	0.0	0.0%
San Francisco	0.809	1.000		1.000	
(I)Cultural Exchange	16.3	-3.1	-19.2%	0.0	0.0%
(I)Livability	40.0	-7.7	-19.2%	-8.2	-20.6%
(I)Environment	54.8	-10.5	-19.2%	0.0	0.0%
(I)Accessibility	29.3	-5.6	-19.3%	0.0	0.0%
(O)Economy	33.9	0.0	0.0%	4.1	12.1%
(O)R&D	28.1	0.0	0.0%	0.0	0.0%
Toronto	0.798	1.000		1.000	
(I)Cultural Exchange	16.9	-3.4	-20.2%	0.0	0.0%
(I)Livability	46.4	-12.1	-26.0%	-8.3	-17.8%
(I)Environment	52.2	-10.6	-20.2%	-12.8	-24.5%
(I)Accessibility	30.8	-6.2	-20.2%	0.0	0.0%
(O)Economy	35.8	0.0	0.0%	4.6	12.7%
(O)R&D	20.1	0.0	0.0%	0.0	0.0%
Chicago	0.754	1.000		1.000	
(I)Cultural Exchange	20.8	-5.1	-24.6%	-1.4	-6.5%
(I)Livability	36.9	-9.1	-24.6%	-9.1	-24.8%
(I)Environment	46.0	-11.3	-24.6%	0.0	0.0%
(I)Accessibility	32.8	-8.7	-26.5%	0.0	0.0%
(O)Economy	31.5	0.0	0.0%	5.1	16.3%
(O)R&D	28.9	0.0	0.0%	0.0	0.0%
Shanghai	0.894	1.000		1.000	
(I)Cultural Exchange	23.9	-2.5	-10.6%	-2.2	-9.3%
(I)Livability	46.4	-9.1	-19.6%	-6.2	-13.3%
(I)Environment	40.8	-4.3	-10.6%	-2.2	-5.4%
(I)Accessibility	31.6	-3.4	-10.6%	0.0	0.0%
(O)Economy	42.3	0.0	0.0%	2.4	5.6%
(O)R&D	11.5	2.5	21.7%	4.6	40.0%
Milan	0.588	1.000		1.000	
(I)Cultural Exchange	20.2	-8.3	-41.2%	-4.8	-24.0%
(I)Livability	49.4	-23.8	-48.2%	-16.4	-33.2%
(I)Environment	46.9	-19.3	-41.2%	-19.6	-41.7%
(I)Accessibility	30.8	-12.7	-41.2%	0.0	0.0%
(O)Economy	27.5	0.0	0.0%	7.1	25.9%
(O)R&D	9.5	0.2	2.1%	7.0	73.4%

DMU	Score	SE model		SE-DFM model	
		Score(θ**)		Score(θ**)	
I/O	Data	Difference	%	Difference $d_{io}^{x*}-s^{-**}$ $d_{ro}^{y*}+s^{+**}$	%
Taipei	0.899	1.000		1.000	
(I)Cultural Exchange	7.3	-0.7	-10.1%	0.0	0.0%
(I)Livability	45.4	-12.6	-27.7%	-10.7	-23.5%
(I)Environment	48.5	-4.9	-10.1%	-3.9	-8.1%
(I)Accessibility	28.4	-7.7	-27.0%	-5.9	-20.7%
(O)Economy	30.2	0.0	0.0%	2.0	6.6%
(O)R&D	16.7	0.0	0.0%	0.0	0.0%
Kuala Lumpur	0.706	1.000		1.000	
(I)Cultural Exchange	14.0	-4.1	-29.4%	0.0	0.0%
(I)Livability	38.7	-11.4	-29.4%	-10.9	-28.1%
(I)Environment	54.2	-15.9	-29.4%	0.0	0.0%
(I)Accessibility	30.5	-9.5	-31.2%	0.0	0.0%
(O)Economy	28.7	0.0	0.0%	4.9	17.2%
(O)R&D	4.4	11.0	250.6%	0.0	0.0%
Bangkok	0.527	1.000		1.000	
(I)Cultural Exchange	22.6	-10.7	-47.3%	0.0	0.0%
(I)Livability	39.4	-18.6	-47.3%	-20.5	-52.0%
(I)Environment	47.5	-22.5	-47.3%	0.0	0.0%
(I)Accessibility	29.1	-13.8	-47.3%	0.0	0.0%
(O)Economy	24.0	0.0	0.0%	7.4	31.0%
(O)R&D	6.9	5.7	82.1%	0.0	0.0%
Sao Paulo	0.671	1.000		1.000	
(I)Cultural Exchange	9.9	-7.1	-71.5%	-6.5	-65.8%
(I)Livability	40.2	-13.3	-33.0%	-7.9	-19.8%
(I)Environment	63.0	-23.0	-36.4%	-15.1	-23.9%
(I)Accessibility	18.8	-6.2	-32.9%	-3.7	-19.7%
(O)Economy	24.0	0.0	0.0%	4.7	19.7%
(O)R&D	3.0	6.7	224.4%	8.6	288.4%
Mumbai	0.637	1.000		1.000	
(I)Cultural Exchange	9.4	-5.9	-63.3%	0.0	0.0%
(I)Livability	42.7	-20.2	-47.2%	0.0	0.0%
(I)Environment	51.1	-18.5	-36.3%	0.0	0.0%
(I)Accessibility	17.4	-6.3	-36.3%	-5.1	-29.3%
(O)Economy	20.7	0.0	0.0%	4.6	22.2%
(O)R&D	3.9	4.1	104.0%	0.0	0.0%
Cairo	0.573	1.000		1.000	
(I)Cultural Exchange	11.9	-5.1	-42.7%	0.0	0.0%
(I)Livability	33.0	-14.1	-42.7%	-14.4	-43.7%
(I)Environment	42.5	-18.1	-42.7%	0.0	0.0%
(I)Accessibility	29.3	-14.3	-48.6%	0.0	0.0%
(O)Economy	19.6	0.0	0.0%	5.3	27.1%
(O)R&D	1.3	9.2	721.5%	0.0	0.0%

Legend: I = Input ; O = Output

We will now offer a concise interpretation of the results presented in these tables. We will take Amsterdam as an illustrative example. From Table 1a, the SE projection shows that, for instance, Amsterdam – in order to achieve a super-efficiency state – should reduce its input volumes Cultural Exchange, Liveability, and Environment by 20.9 per cent, and Accessibility by 26.4 per cent in order to become efficient. On the other hand, the SE-DFM projection results show that a reduction in the Liveability of 19.0 per cent and an increase in the Economy of 11.7 per cent is required to become efficient. It should be added that in a deterministic DEA model these findings are numerically correct, but that in policy practice such accurate adjustments will hardly be achieved. Nevertheless, this information is indicative for the direction and intensity of necessary policy handles in a city to become efficient.

For the sake of illustration, a comparison of the projection results of Amsterdam is presented in Figure 10. This result clearly shows that a different – and more efficient and effective – solution is available than the SE projection to reach the efficiency frontier.

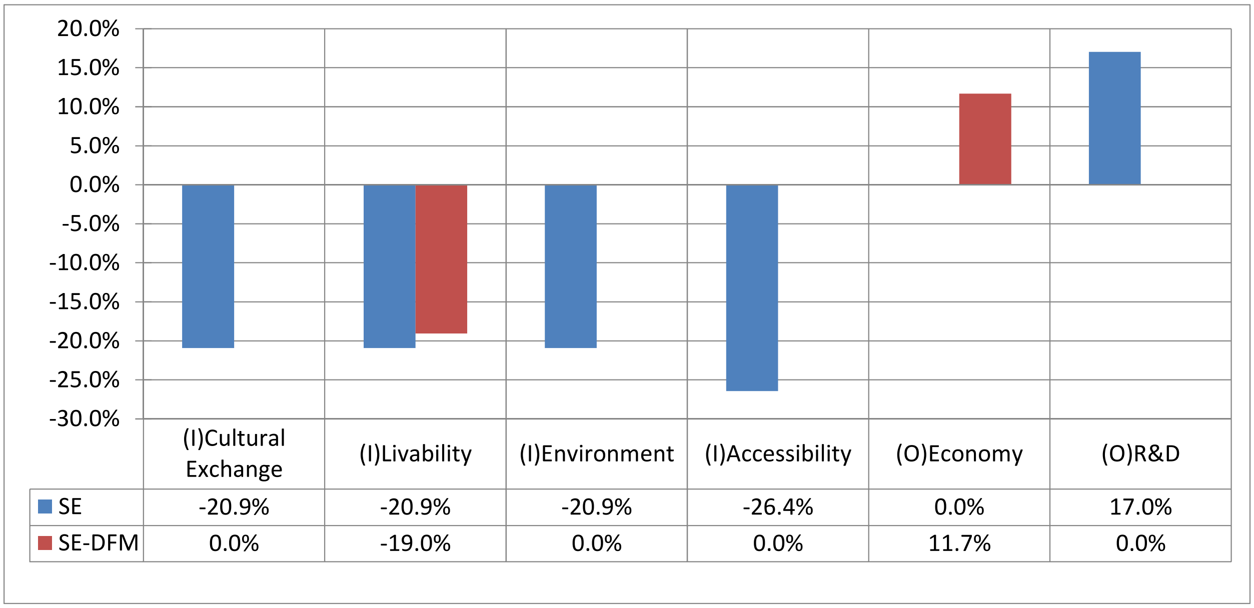

Figure 10. Projection results of Amsterdam, based on SE and SE-DFM

5.2 Stepwise efficiency-improving projection based on SE and SE-DFM models

The stepwise efficiency-improvement projection results based on the SE and SE-DFM model for inefficient cities are presented in Tables 2a and 2b.

In Tables 2a and 2b, it appears that the ratios of change in the Stepwise SE-DFM projection are smaller than those in the Stepwise SE projection, as might be expected. In Tables 2a and 2b, this particularly applies to Sao Paulo, Brussels, Mumbai, and Kuala Lumpur, which are non-slack type DMUs (i.e. s^{-**} and s^{+**} are zero). Apart from the practicality of such a solution, the models show clearly that a different – and perhaps more efficient – solution is available than the Stepwise SE projection to reach the efficiency frontier.

The more advanced Stepwise SE-DFM model is able to present a more realistic efficiency-improvement result, which we can compare with the results of Tables 1b and b. For instance, the SE-DFM results in Table 1b show that Mumbai should reduce its accessibility indicator by 29.3 per cent, and increase the Economy by 22.2 per cent in order to become entirely efficient. On the other hand, the Stepwise SE-DFM results in Table 2b show that a reduction in Accessibility of 3.1 per cent, and an increase in the Economy of 1.3 per cent are required to become efficient (this means that Mumbai can attain the E4 level efficient frontier moving up from the E5 level). It should be noted that also in this case the same proviso on the interpretation holds, as indicated above.

Table 2a. Stepwise efficiency-improvement projections based on SE and DFM

	DMU	Score	Stepwise SE Score(θ**)		Stepwise SE-DFM Score(θ**)	
	I/O	Data	Difference	%	Difference $d_{io}^{x*}-s^{-**}$ $d_{ro}^{y*}+s^{+**}$	%
E3	Vancouver	0.999	1.000		1.000	
	(I)Cultural Exchange	12.4	-2.6	-20.5%	-2.6	-25.9%
	(I)Livability	60.7	-22.0	-36.2%	-22.0	-56.7%
	(I)Environment	56.4	-0.1	-0.1%	0.0	0.0%
	(I)Accessibility	25.9	0.0	-0.1%	0.0	-0.1%
	(O)Economy	34.6	0.0	0.0%	0.0	0.1%
	(O)R&D	17.8	0.0	0.0%	0.0	0.0%
	Osaka	0.998	1.000		1.000	
	(I)Cultural Exchange	12.9	0.0	-0.3%	0.0	0.0%
	(I)Livability	51.6	-10.0	-19.3%	-9.8	-23.6%
	(I)Environment	52.8	-0.1	-0.3%	-0.1	-0.2%
	(I)Accessibility	30.5	-0.1	-0.3%	0.0	0.0%
	(O)Economy	34.0	0.0	0.0%	0.1	0.2%
	(O)R&D	24.1	0.0	0.0%	0.0	0.0%
	Sydney	0.995	1.000		1.000	
	(I)Cultural Exchange	23.2	-9.8	-42.3%	0.0	0.0%
	(I)Livability	45.2	-2.3	-5.0%	0.0	0.0%
	(I)Environment	60.4	-0.3	-0.5%	0.0	0.0%
	(I)Accessibility	29.7	-0.1	-0.5%	-8.1	-27.6%
	(O)Economy	37.8	0.0	0.0%	0.1	0.3%
	(O)R&D	22.2	0.0	0.0%	3.4	15.3%
	Paris	0.951	1.000		1.000	
	(I)Cultural Exchange	51.3	-2.5	-4.9%	0.0	0.0%
	(I)Livability	55.6	-15.5	-27.8%	-14.4	-35.9%
	(I)Environment	56.2	-2.8	-4.9%	-1.5	-2.9%
	(I)Accessibility	57.9	-9.5	-16.5%	-7.8	-16.0%
	(O)Economy	42.9	1.4	3.4%	2.9	6.6%
	(O)R&D	40.3	0.0	0.0%	1.0	2.5%
	Chicago	0.948	1.000		1.000	
	(I)Cultural Exchange	20.8	-1.1	-5.2%	0.0	0.0%
	(I)Livability	36.9	-3.6	-9.7%	-2.2	-6.5%
	(I)Environment	46.0	-2.4	-5.2%	-1.4	-3.3%
	(I)Accessibility	32.8	-2.8	-8.5%	-1.8	-5.9%
	(O)Economy	31.5	0.0	0.0%	1.4	4.3%
	(O)R&D	28.9	0.0	0.0%	0.0	0.0%
	Toronto	0.938	1.000		1.000	
	(I)Cultural Exchange	16.9	-1.1	-6.2%	0.0	0.0%
	(I)Livability	46.4	-7.0	-15.1%	-3.5	-9.0%
	(I)Environment	52.2	-3.2	-6.2%	-3.0	-6.2%
	(I)Accessibility	30.8	-1.9	-6.2%	0.0	0.0%
	(O)Economy	35.8	0.0	0.0%	1.4	4.0%
	(O)R&D	20.1	0.0	0.0%	0.0	0.0%
	Frankfurt	0.937	1.000		1.000	
	(I)Cultural Exchange	10.5	-0.7	-6.3%	0.0	0.0%
	(I)Livability	45.2	-2.8	-6.3%	-2.2	-5.3%
	(I)Environment	66.5	-4.2	-6.3%	0.0	0.0%
	(I)Accessibility	38.5	-10.5	-27.2%	-8.7	-30.9%
	(O)Economy	38.5	0.0	0.0%	1.2	3.2%
	(O)R&D	13.8	3.4	24.7%	5.7	33.4%

	DMU	Score	Stepwise SE Score(θ**)		Stepwise SE-DFM Score(θ**)	
	I/O	Data	Difference	%	Difference $d_{io}^{x*}-s^{-**}$ $d_{ro}^{y*}+s^{+**}$	%
E4	Vienna	0.994	1.000		1.000	
	(I)Cultural Exchange	24.9	-3.8	-15.4%	-3.8	-18.2%
	(I)Livability	47.5	-0.3	-0.6%	0.0	0.0%
	(I)Environment	64.3	-5.5	-8.6%	-5.3	-9.1%
	(I)Accessibility	28.7	-0.2	-0.6%	-0.1	-0.3%
	(O)Economy	36.7	0.0	0.0%	0.1	0.3%
	(O)R&D	15.6	5.6	35.9%	5.6	26.6%
	Amsterdam	0.983	1.000		1.000	
	(I)Cultural Exchange	17.9	-0.3	-1.7%	0.0	0.0%
	(I)Livability	48.2	-0.8	-1.7%	0.0	0.0%
	(I)Environment	65.3	-1.1	-1.7%	-1.1	-1.7%
	(I)Accessibility	41.0	-0.7	-1.8%	-0.9	-2.2%
	(O)Economy	40.1	0.0	0.0%	0.3	0.9%
	(O)R&D	18.5	5.3	28.5%	5.4	22.8%
	Sao Paulo	0.974	1.000		1.000	
	(I)Cultural Exchange	9.9	-0.3	-2.7%	0.0	0.0%
	(I)Livability	40.2	-1.1	-2.7%	0.0	0.0%
	(I)Environment	63.0	-24.0	-38.1%	0.0	0.0%
	(I)Accessibility	18.8	-0.5	-2.7%	-0.5	-2.8%
	(O)Economy	24.0	0.0	0.0%	0.3	1.3%
	(O)R&D	3.0	9.6	322.3%	0.0	0.0%
	Brussels	0.898	1.000		1.000	
	(I)Cultural Exchange	21.4	-2.2	-10.3%	0.0	0.0%
	(I)Livability	46.9	-4.8	-10.2%	0.0	0.0%
	(I)Environment	52.7	-5.4	-10.2%	-4.4	-9.4%
	(I)Accessibility	34.4	-3.5	-10.2%	0.0	0.0%
	(O)Economy	32.8	0.0	0.0%	1.8	5.4%
	(O)R&D	14.7	6.5	44.4%	0.0	0.0%
	Berlin	0.882	1.000		1.000	
	(I)Cultural Exchange	28.2	-7.0	-24.8%	-6.7	-31.5%
	(I)Livability	48.7	-8.5	-17.4%	-8.7	-21.6%
	(I)Environment	66.8	-14.0	-20.9%	-15.0	-28.3%
	(I)Accessibility	32.6	-3.9	-11.8%	-2.1	-7.1%
	(O)Economy	33.8	0.0	0.0%	0.0	0.0%
	(O)R&D	22.7	0.0	0.0%	2.3	10.3%

Table 2b. Stepwise efficiency-improvement projections based on SE and DFM

	DMU	Score	Stepwise SE Score(θ**)		Stepwise SE-DFM Score(θ**)	
	I/O	Data	Difference	%	Difference $d_{io}^{x*}-s^{-**}$ $d_{ro}^{y*}+s^{+**}$	%
E5	Mumbai	0.973	1.000		1.000	
	(I)Cultural Exchange	9.4	-0.2	-2.7%	0.0	0.0%
	(I)Livability	42.7	-10.2	-23.9%	0.0	0.0%
	(I)Environment	51.1	-1.4	-2.7%	0.0	0.0%
	(I)Accessibility	17.4	-0.5	-2.7%	-0.5	-3.1%
	(O)Economy	20.7	0.0	0.0%	0.3	1.3%
	(O)R&D	3.9	0.2	4.2%	0.0	0.0%
	Madrid	0.875	1.000		1.000	
	(I)Cultural Exchange	21.4	-2.7	-12.5%	0.0	0.0%
	(I)Livability	48.6	-6.5	-13.5%	-0.8	-1.8%
	(I)Environment	60.6	-7.6	-12.5%	-5.4	-10.3%
	(I)Accessibility	35.4	-4.4	-12.5%	0.0	0.0%
	(O)Economy	32.1	0.0	0.0%	2.1	6.7%
	(O)R&D	10.9	3.4	31.4%	4.5	31.3%
	Milan	0.942	1.000		1.000	
	(I)Cultural Exchange	20.2	-2.3	-11.3%	-1.7	-9.7%
	(I)Livability	49.4	-10.1	-20.4%	-8.9	-22.6%
	(I)Environment	46.9	-2.7	-5.8%	-1.4	-3.2%
	(I)Accessibility	30.8	-1.9	-6.3%	-1.1	-3.7%
	(O)Economy	27.5	0.0	0.0%	0.8	3.0%
	(O)R&D	9.5	2.8	29.5%	3.2	25.8%
	Kuala Lumpur	0.930	1.000		1.000	
	(I)Cultural Exchange	14.0	-1.0	-7.0%	0.0	0.0%
	(I)Livability	38.7	-2.7	-7.0%	0.0	0.0%
	(I)Environment	54.2	-4.3	-8.0%	0.0	0.0%
	(I)Accessibility	30.5	-2.1	-7.0%	-2.3	-8.1%
	(O)Economy	28.7	0.0	0.0%	1.0	3.6%
	(O)R&D	4.4	7.8	177.8%	0.0	0.0%

	DMU	Score	Stepwise SE Score(θ**)		Stepwise SE-DFM Score(θ**)	
	I/O	Data	Difference	%	Difference $d_{io}^{x*}-s^{-**}$ $d_{ro}^{y*}+s^{+**}$	%
E6	Bangkok	0.933	1.000		1.000	
	(I)Cultural Exchange	22.6	-7.5	-33.1%	-6.9	-45.3%
	(I)Livability	39.4	-2.6	-6.7%	0.0	0.0%
	(I)Environment	47.5	-3.2	-6.7%	-2.6	-5.8%
	(I)Accessibility	29.1	-2.8	-9.6%	-1.8	-6.9%
	(O)Economy	24.0	0.0	0.0%	0.9	3.7%
	(O)R&D	6.9	0.0	0.0%	0.0	0.0%
	Cairo	0.859	1.000		1.000	
	(I)Cultural Exchange	11.9	-1.7	-14.1%	0.0	0.0%
	(I)Livability	33.0	-5.3	-16.0%	-1.5	-5.5%
	(I)Environment	42.5	-6.0	-14.1%	-3.9	-10.7%
	(I)Accessibility	29.3	-8.4	-28.5%	-6.6	-31.3%
	(O)Economy	19.6	0.0	0.0%	1.5	7.6%
	(O)R&D	1.3	2.3	178.6%	3.3	91.9%

6. Policy Lessons and Suggestions

Our DEA analysis has aimed to shed new light on the rankings of world cities. Most comparative studies are based on an aggregate (weighted or unweighted) average of a set of background factors that have been translated into operational indicators. The approach adopted in the present study has focused attention much more on the efficiency and productivity of large cities, using a comparative data set. These research presented in the present study has offered interesting insights into the benchmark position of world cities, based on an extensive data set. Our findings reveal striking differences compared with standard ranking and benchmarking procedures. In particular, the new methods to arrive at unambiguous DEA ranking results provide promising findings.

The Stepwise SE-DFM model provides the policy maker with practical and transparent solutions that are available in the SE-DFM projection to reach the nearest upper-level efficiency frontier. These results offer a meaningful contribution to decision support and planning for the efficiency improvement of strategic urban policy. And therefore, this Stepwise SE-DFM model may become a policy vehicle that may have great added value for operational decision making and planning in cities. Clearly, cities have the possibility to increase their potential. This improvement potential differs for each city, but our results offer operational guidelines on a case-by-case city basis.

In this paper we have in particular presented a new methodology, the SE-DFM and Stepwise SE-DFM model, which integrates a Super-Efficiency model, a DFM model and a CD model. The new method minimizes the distance friction for each input and output separately. As a result, the combined reductions in inputs and increases in outputs that are necessary to reach an efficiency frontier are smaller than in the standard model. Furthermore, the new model could be adapted to reflect realistic conditions in an efficiency-improvement projection. In addition, the stepwise projection allows DMUs to include various levels of ambition regarding the ultimate performance in their strategic judgment. Clearly, our deterministic DEA modeling results have to be interpreted with some caution, as the level of precision implied by our findings is in practical situations not achievable. Nevertheless, our results offer an indication of the level of intensity and the direction of policy efforts that are needed to upgrade the efficiency profile of world cities. In conclusion, our Stepwise SE-DFM model is able to present a more realistic efficiency-improvement urban policy strategy, and may thus provide a significant support contribution to decision making and planning for the efficiency improvement of the relevant agents involved.

References

Acs, Z.J., F.R. FitzRoy and I. Smith, High Technology Employment and R&D in Cities: Heterogeneity vs. Specialization, *The Annals of Regional Science*, vol. 36, 2002, pp. 373-386.

Anderson P. and N. Petersen, A Procedure for Ranking Efficient Units in Data Envelopment Analysis, *Management Science*, vol. 39, 1993, pp. 1261-1264.

Arribas-Bel, D., P. Nijkamp, and H. Scholten (2011). Multidimensional Urban Sprawl in Europe: A Self-organizing Map Approach, *Computers, Environment and Urban Systems*, 35(4):263 - 275.

Charnes, A., W. Cooper, and E. Rhodes, Measuring the efficiency of decision making units, *European Journal of Operational Research*, vol. 2, 1978, pp. 429-444.

Cheshire, P.C., and S. Magrini, Urban Growth Drivers in a Continent of Sticky People and Implicit Boundaries, *Journal of Economic Geography*, vol. 9, 2009, pp. 85-115.

Geenhuizen, M. van, and P. Nijkamp, *The Creative Knowledge City*, Edward Elgar, Cheltenham, 2011.

Glaeser E. and W.R. Kerr, Local Industrial Conditions and Entrepreneurship: How Much of the Spatial Distribution Can We Explain?, *Journal of Economics and Management Strategy*, vol. 18, no. 3, 2009, pp. 623-663.

Grosveld, H., *The Leading Cities of the World and Their Competitive Advantages*, PhD dissertation, University of Amsterdam, 2002.

Institute for Urban Strategies, *Global Power City Index*, The Mori Memorial Foundation, Tokyo, 2010 (http://www.mori-mfoundation.or.jp/english/research/project/6/pdf/GPCI2009_English.pdf).

Kourtit, K., P. Nijkamp and R. Stough (eds), *Drivers of Innovation, Entrepreneurship and Regional Dynamics*, Springer-Verlag, Berlin, 2011.

Kourtit, K., P. Nijkamp and D. Arribas, Smart Cities Perspective – a Comparative European Study by Means of Self-Organizing Maps, *Journal Innovation*, 2012a (forthcoming).

Kourtit, K., D. Arribas and P. Nijkamp, Benchmarking of World Cities through Self-organizing Maps, *Cities*, 2012b (forthcoming).

Sassen, S., *The Global City*, Princeton University Press, Princeton NJ, 1991.

Seiford, L.M. and J. Zhu, Context-dependent Data Envelopment Analysis – Measuring Attractiveness and Progress, *Omega,* vol. 31, 2003, pp. 397.

Shefer, D. and A. Frenkel, Local Milieu and Innovations: Some Empirical Results, *The Annals of Regional Science*, vol. 32, 1998, pp. 185-200.

Suzuki, S., P. Nijkamp, P. Rietveld and E. Pels, A Distance Friction Minimization Approach in Data Envelopment Analysis: A Comparative Study on Airport Efficiency, *European Journal of Operational Research*, vol. 207, 2010, pp.1104-1115.

Suzuki,S., P. Nijkamp and P. Rietveld, Regional Efficiency Improvement by Means of Data Envelopment Analysis through Euclidean Distance Minimization Including Fixed Input Factors: An Application to Tourist Regions in Italy, *Papers in Regional Science,* vol. 90, no. 1, 2011, pp. 67-89.

Taylor, P.J., P. Ni, B. Derudder, M. Hoyler, J. Huang, F. Lu, K. Pain, F. Witlox, X. Yang, D. Bassens and W. Shen, Measuring the World City Network: New Developments and Results, *GaWC Research Bulletin 300*, 2009.

Tone, K., A Slacks-Based Measure of Efficiency on Data Envelopment Analysis, *European Journal of Operational Research*, vol. 130, 2001, pp. 498-509.

Tone, K., 2002. A Slacks-Based Measure of Super-Efficiency in Data Envelopment Analysis. *European Journal of Operational Research,* vol. 143, pp. 32-41.

ANNEX. GPCI-2010 on attribute categories of World Cities