The Robustness of Performance Rankings of Asia-Pacific Super Cities

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Abstract

Over the past decades, the Asia-Pacific Rim has exhibited an unprecedented high degree of economic and geographic dynamics. Clearly, cities in this region display a heterogeneity in terms of economic performance, technological innovativeness, environmental conditions, and cultural recognition and interaction. It is, therefore, interesting to develop an efficiency ranking of the multi-dimensional performance of these large cities so as to identify '*super cities*'. The first aim of this paper is now to undertake a multi-faceted performance ranking of large cities in the Asia-Pacific region by using a DEA (Data Envelopment Analysis). However, there appears to be a wide variety of DEAs in the recent literature. And therefore, a second aim of the present paper is to perform a sensitivity analysis on the type of DEA employed, so as to test the robustness of the base ranking obtained from a standard DEA. A third aim of the paper is related to the question how much the ranking obtained by a DEA is influenced by the internal characteristics of the underlying data system. This leads to a sensitivity analysis of the precision or nature of the data used in the DEA. These three aims of the research will be empirically addressed by using a comprehensive data set on 7 quantitative main indicators regarding economic performance, technological innovativeness, environmental conditions, and cultural recognition and interaction for 13 Asia-Pacific super cities.

Keywords: Asia-Pacific Super Cities, Efficiency ranking, DEA (Data Envelopment Analysis), Robustness.

JEL: R11, O18,

1. Search for Super Cities

Our planet is increasingly showing the signs of an urbanized geographical settlement structure. This '*New Urban World*' (see Kourtit 2014, 2015) marks a historical break-through compared to previous settlement patterns: rurality as a dominant geographical characteristic of our world is replaced by urbanity. This historical mega-trend manifests itself most clearly in the share of people in a country or region that resides in a city or urban (or metropolitan) area. This urbanization rate has shown a rapid rise in the past two centuries; it rose from 10 to 15 percent in the pre-Napoleonic time to over 50 percent world-wide, with an urbanization degree of about 70 to 80 percent in most OECD countries. And for the time being, there is no foreseeable standstill to this mega-trend. Various projections indicate that by the middle of this century the urbanization rate on our planet will have increased to over 75 percent.

This drastic change in the geography of our world is not just a neutral spatial re-distribution of people. It is the consequence of major socio-economic, technological, logistic, climatological, political and institutional changes in our world, in which the economies of agglomeration have become a powerful force for a rise in geographic density, proximity and connectivity (see Nijkamp 2016). In this context, urban agglomerations have become the engines of economic, technological, political and social power. Consequently, cities are not passive actors in a dynamic and open world geography. Instead, the awareness is rapidly growing that major agglomerations – especially mega-cities with more than 10 mln inhabitants – become the new 'control and command centres' of our world (Sassen 1991). Such large urban areas become contemporaneous influential magnets for economic activity, in combination with their creative, cognitive and innovative ability. Their historically centripetal and centrifugal impact is now extended from their traditional hinterlands to a world-wide scale in a globalizing economy.

The consequence of the above sketched development is that cities have turned into active players in the global geography of our world, with the inevitable result that they will have to maintain or expand their position. In tandem with the world-wide globalization trend, urban agglomerations have nowadays a permanent drive to perform better, so as to increase their global recognition or their place on the world-wide economic performance ladder. Indeed, cities have become performance-driven agents which are involved – directly or indirectly – in a global competition in terms of recognition or achievement. We call this trend here the 'search for super cities', viz. the ambition of urban agglomerations in our world to perform better than others.

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

The main aim of the paper is now to test the robustness of DEA results – applied to the performance of various Asian-Pacific cities (13 in total) – against variations in the number of outputs, the number of inputs, the number of actors and the type of DEA used. In the present paper, a very detailed and extensive data base on Asian-Pacific cities will be used, with a view to explore whether changes in the data base or in the methodological base will lead to a change in the performance ranking of the Asian-Pacific cities investigated.

The paper is organized as follows. After this introductory section, we will offer in Section 2 a concise sketch of urban dynamics in the Asia-Pacific region, while we will also introduce DEA as a methodological instrument to perform a sensitivity analysis on the efficiency ranking of the 13 Asian-Pacific cities under consideration. Next, Section 3 will be devoted to a more detailed description of the urban data base used, which originates from the so-called GPCI data system provided by the Mori Memorial Foundation in Japan. The core of the analysis is formed by Section 4, which contains a description of the various sensitivity analyses to be carried out on the data and on the methods, and by Section 5, which provides all results from the sensitivity analyses and interprets these findings. The final section offers conclusions and prospects for further research.

2. Data Envelopment Analysis as a Tool for Tracing Asian-Pacific Super Cities

The Asian-Pacific Rim has over the past decades shown an unprecedented multi-faceted dynamics. From a largely underdeveloped region after WWII, it has turned into one of the main vibrant heartlands of the global economy. The initially selective set of the previous 'Asian tigers' in the 1980s has gradually been extended towards a modern competitive region with powerful mega-economies such as China and India. This development has deeply impacted the world economy, and the economic geography of our world.

The dynamics of the Asia-Pacific area is also reflected in the growth of urban agglomerations in this region. The rise of mega-cities (e.g., Tokyo, Beijing, Shanghai, Singapore) is a clear sign of the underlying far-reaching economic, social, political and demographic transformations of the countries involved. All such cities are increasingly becoming economic and technological power houses with a world-wide impact. At the same time, they are involved in a fierce competition so as to be recognized as a high-performing super city, in terms of economic performance, technological innovativeness, environmental conditions, and cultural recognition and interaction. Through smart specialization and creative development they try to climb as high as possible on the global competitiveness ladder. Despite a foreseen population decline in various countries (e.g., China, Japan), it turns out that their mega-cities are still rising (to the detriment of rural areas).

As mentioned in the introduction of this paper, DEA has become an established scientific analysis instrument to assess the compound performance of agents (including cities), by estimating the generalized efficiency of these agents (i.e., cities) through the calculation of combined output and input achievements. Various introductions into DEA and applications to urban 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 Susuki anf Nijkamp (2017). This large number of applied studies shows that an operational analysis of urban efficiency in a competitive environment is an important but also intriguing research topic on the regional science literature.

We will apply in the present study DEA as a tool to arrive at a ranking of various Asian-Pacific cities (13 in total). We will perform a sensitivity analysis on the data base for these Asian-Pacific cities, along various relevant dimensions of completeness and accuracy of the information. In addition, we will use 2 types of DEA methodology, namely, the Charnes, Cooper and Rhodes approach (usually abbreviated as the CCR-model) and the Slack-Based Measure (SBM) model, by employing both models for a so-called Super-Efficiency DEA method. The basic CCR-model was originally developed by Charnes et al. (1978). Over the past decades, a wide range of adjustments and revisions has been implemented, so as to cope with weak elements, limitations or specific needs of DEA model applications. A specific feeble element of a standard CCR-model is that all efficient actors have an identical score, equal to 1.0.

An interesting new endeavour was developed by Anderson and Petersen (1993) who developed the Super-Efficiency (SE hereafter) model based on the initial CCR model so as to arrive at a complete ranking of all efficient DMUs (even though they have all an efficiency score equal to 1.0). The efficiency scores from an SE-model are then obtained by eliminating the data on the DMU to be evaluated from the solution set to examine its relative effect. These values are then used to rank the initial efficient DMUs, and consequently, efficient DMUs may then obtain an efficiency score above 1.0, while the scores of all inefficient DMUs remain identical and below 1.0.

We will also use here an adjusted version of a standard DEA model, namely a Slack-Based Measure (SBM) model which was developed by Tone (2001). The main distinction between the standard CCR model and the SBM model is related to the use of a radial-type model and non-radial type model, respectively. A shortcoming of a radial model is that the neglect of slacks in computing the efficiency score. Consequently, the radial-type model may bias and overestimate the efficiency score. In contrast, the non-radial type models including the SBM-model deal with a slack directory. Hence, an SBM model can mitigate the overestimating problem. The SBM model was also developed as an SE type model (see Tone 2002). We will use in our analysis both the CCR-input and the SBM-input type model based on an SE model.

In the next section we will first introduce the GPCI data base and the selection of the 13 Asian-Pacific cities, followed by a sensitivity experiment of various types of DEA models.

3. The Data Base and Analytical Framework for the Asian-Pacific Cities

For a systematic operational comparison of Asian-Pacific cities' performance outcomes, our empirical approach uses a unique and extensive data set on measurable indicators for the cities under consideration, viz. the Global Power City Index (GPCI), produced by the Institute for Urban Strategies and organized by the Mori Memorial Foundation (2016) in Tokyo. We will use here very recent data for the year 2016, which offer a great potential for a comparative benchmark analysis for the Asian-Pacific large cities. The GPCI database will thus be used here as a strategic tool to evaluate and to rank the comprehensive strategic power determinants of 13 major cities in this region, in terms of their strengths and their weaknesses.

The GPCI data base is a multi-annual world-wide data system on large cities, in which the comprehensive performance scores and rankings of these global cities are based on six main assessment categories, namely: *Economy*, *Research & Developmen*t, *Cultural Interaction*, *Livability*, *Environment*, and *Accessibility*. Each of these main indicators classes is subdivided into a set of appropriate and measurable sub-indicators, so that finally a strictly consistent and carefully tested database on approx. 70 sub-indicators related to many world cities (40 in total) is created. This database is published annually since 2009. The 13 Asia-Pacific cities used in our analysis are taken from this database. All further details are available in the above mentioned GPCI report.

In our presentation we refer now to the "score by indicator" datasets in the GPCI report. Most of these indicator data are converted into a standardized indicator value, falling in between 100 and 0, so that the data can be evaluated according to a uniform standard measurement. The highest performance of an indicator receives a score equal to 100, and the poorest a score of 0. However, since a higher value for cost indicators (such as for risk and CO2 emission) necessarily means essentially a low assessment score, the value assignment scale was converted for these indicators (i.e., the highest score of a cost item is 0 and the lowest score is 100).

We will now use for our benchmark analysis a selected set of relevant input and output data of the GPCI-2016 study for a set of 13 large Asian-Pacific cities to evaluate and compare their economic performance, technological innovativeness, environmental conditions, and cultural interaction efficiency. The DMUs (decision-making units or cities) used in our comprehensive analysis are listed in Table 1.

Table 1. List of DMUs

No	DMUs	No	DMUs
1	Bangkok	7	Osaka
2	Beijing	8	Seoul
3	Fukuoka	9	Shanghai
4	Hong Kong	10	Singapore
5	Kuala Lumpur	11	Sydney
6	Mumbai	12	Taipei
		13	Tokyo

As shown in Table 1, we have selected as relevant DMUs the available set of 13 Asian-Pacific cities from the GPCI system. For our comparative performance analysis of the cities under consideration, we consider as evaluation criteria: economic performance, technological innovativeness, environmental conditions, and cultural recognition and interaction. Based on this viewpoint, we will select and introduce now 3 relevant input and 2 relevant output items as follows:

Input (I):

- (I1) Total Employees (EMP, hereafter)
- (I2) Research and Development (R&D) Expenditures (R&D, hereafter)
- (I3) Cultural Interaction (The score of this item was calculated by adding up the indicator scores in Table 2) (CI, hereafter)

Output (O):

- (O1) GDP
- (O2) Environment (The score of this item was calculated by adding up the indicator scores in Table 3) (ENV, hereafter)

Table 2. Indicators of Cultural Recognition and Interaction

Indicator Type	Indicator
Cultural Resources	Environment of Creative Activities
	Number of World Heritage Sites (within 100km Area)
	Opportunities of Cultural, Historical and Traditional Interaction
Facilities for Visitors	Number of Theatres and Concert Halls
	Number of Museums
	Number of Stadiums
Attractiveness to Visitors	Number of Guest Rooms of Luxury Hotels
	Number of Hotels
	Level of Satisfaction for Shopping
	Level of Satisfaction for Dining
Volume of Interaction	Number of Foreign Residents
	Number of Visitors from Abroad
	Number of International Students

Table 3. Indicator of Environment

Indicator[1]
CO_2 Emissions
Density of Suspended Particulate Matter (SPM)
Density of Sulfur Dioxide (SO_2), Density of Nitrogen Dioxide (NO_2)

4. Sensitivity Analysis for DEA Applications

4.1 A sensitivity analysis matrix

As mentioned above, one of the main challenges of the present study is to perform a robustness analysis on the application of DEA to 13 Asian-Pacific cities. We will undertake this robustness analysis in two steps, viz. (A) a sensitivity analysis on several methodological variants of a DEA, and (B) a sensitivity analysis on the number of input items and output items, and on the number of DMUs (or cities).

A. Sensitivity of DEA regarding methodological features

In this part of the study, we will address the impact of shifts in methodological approaches to a DEA. We will pay particular attention to the following sensitivity experiments, using two types of super-efficient (SE) DEA models:

- A1: SE-CCR (a sensitivity test on the effect of an SE-CCR model for the city rankings)
- A2: SE-SBM (a sensitivity test on the impact of an SE-SBM model on the city rankings)

B. Sensitivity of DEA for shifts in information base

We will now successively undertake the following experiments on the sensitivity of DEA results in relation to variations on the information side of the DEA used:

- B1: Input elimination (the change in DEA outcomes as a consequence of a change in the number of input items in the DEA)

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[1] All data – and more details – can be found in the above mentioned GPCI report (2016).

- B2: Output elimination (the change in DEA results as a consequence of a change in the number of output items in the DEA)
- B3: Efficient DMUs elimination (the change in DEA results as a consequence of a change in the number of DMUs in the DEA; this holds only for efficient DMUs). Clearly, if we eliminate inefficient DMUs from the DMU set, the efficiency scores for the DMUs will not change. Conversely, if we eliminate any efficient DMU, the efficiency scores will certainly change to a greater or lesser extent.

It should be noted that the above mentioned sensitivity analyses described ad A and B can be performed separately, but they can also be performed in various combinations of A and B, as is illustrated in the following integral sensitivity matrix (see Table 4).

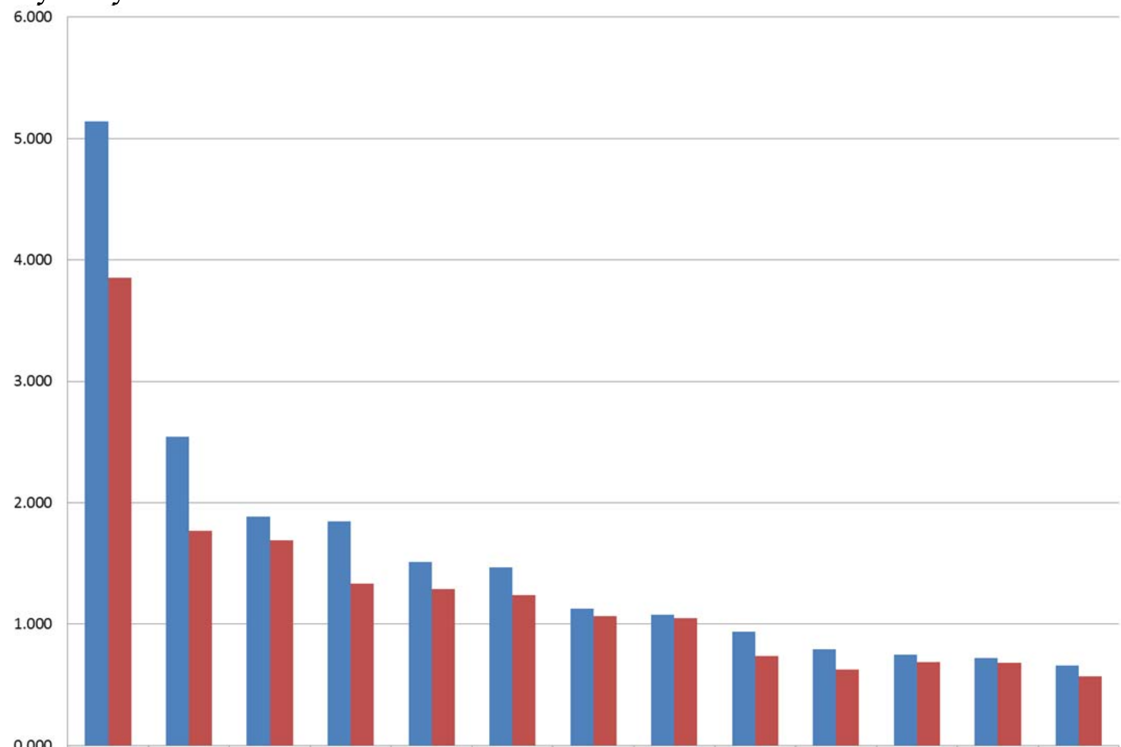
Table 4. A sensitivity analysis matrix for DEA

A: Methodological Sensitivity / B: Information Sensitivity	A1:Super Efficiency (SE)-CCR	A2: Super Efficiency (SE)-SBM
B1:3I(Input)-2O(Output) -13DMUs	SE-CCR-3I-2O-13DMUs	SE-SBM-3I-2O-13DMUs
2I(with elimination on CI)-2O – 13DMUs	SE-CCR-2I(eli CI)-2O	SE-SBM-2I(eli CI)-2O
2I(with elimination on R&D)-2O – 13DMUs	SE-CCR-2I(eli R&D)-2O	SE-SBM-2I (eli R&D)-2O
1I(with elimination on CI and R&D)-2O -13DMUs	SE-CCR-1I (eli CI and R&D)-2O	SE-SBM-1I (eli CI and R&D)-2O
B2: 3I-1O(with elimination on GDP) – 13DMUs	SE-CCR-3I-1O(eli GDP)	SE-SBM-3I-1O (eli GDP)
3I-1O(with elimination on ENV) – 13DMUs	SE-CCR-3I-1O(eli ENV)	SE-SBM-3I-1O(eli ENV)
B3:3I(Input)-2O(Output) -12DMUs (with elimination on Bangkok)	SE-CCR-eli BAN	SE-SBM-eli BAN
3I(Input)-2O(Output)-12DMUs (with elimination on Fukuoka)	SE-CCR-eli FUK	SE-SBM-eli FUK
3I(Input)-2O(Output)-12DMUs (with elimination on Hong Kong)	SE-CCR-eli HON	SE-SBM-eli HON
3I(Input)-2O(Output)-12DMUs (with elimination on Kuala Lumpur)	SE-CCR-eli KUA	SE-SBM-eli KUA
3I(Input)-2O(Output)-12DMUs (with elimination on Mumbai)	SE-CCR-eli MUM	SE-SBM-eli MUM
3I(Input)-2O(Output)-12DMUs (with elimination on Sydney)	SE-CCR-eli SYD	SE-SBM-eli SYD
3I(Input)-2O(Output)-12DMUs (with elimination on Taipei)	SE-CCR-eli TAI	SE-SBM-eli TAI
3I(Input)-2O(Output)-12DMUs (with elimination on Tokyo)	SE-CCR-eli TOK	SE-SBM-eli TOK

4.2 Results of sensitivity analysis in SE-CCR and SE-SBM models

The efficiency evaluation result for the 13 Asian-Pacific cities based respectively on the SE-CCR model and the SE-SBM model using the abovementioned 3Input-2Output database is presented in Figure 1. The rankings for both types of models appear to be entirely identical. Also the pattern of efficient and inefficient cities among these 13 cities is entirely robust. From Figure 1, it can also be seen that Kuala Lumpur, Bangkok, Hong Kong, Sydney, Fukuoka, Tokyo, Mumbai and Taipei are regarded as super-efficient cities. In contrast, Shanghai, Beijing, Osaka, Singapore and Seoul are evaluated as inefficient or less efficient cities. These cities may need an additional boost and an extra effort for improving their performance.

It also can be seen that the rank orders for the pairs of SE-CCR-3I-2O-13DMUs and SE-SBM3I-2O-13DMUs offer completely identical results. These results demonstrate a robustness of performance rankings of the Asia-Pacific Super Cities from the viewpoint of a methodological sensitivity. This result for these 2 cases may be used as a comparative benchmark for our sensitivity analysis.



	Kuala Lumpur	Bangkok	Hong Kong	Sydney	Fukuoka	Tokyo	Mumbai	Taipei	Shanghai	Beijing	Osaka	Singapore	Seoul
SE-CCR-3I-2O-13DMUs	5.140	2.541	1.884	1.846	1.509	1.467	1.126	1.075	0.940	0.793	0.746	0.718	0.659
SE-SBM-3I-2O-13DMUs	3.852	1.767	1.691	1.332	1.287	1.239	1.064	1.049	0.740	0.625	0.690	0.682	0.570

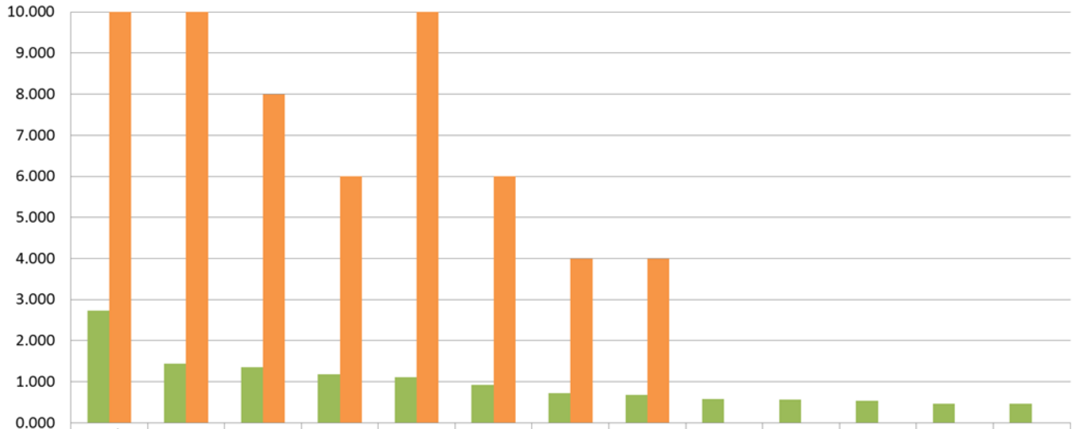
Figure 1. Efficiency scores based on the SE-CCR and SE-SBM model

4.3 Results of sensitivity analysis on information variation

4.3.1 Sensitivity analysis for input and output items elimination

We will now carry out a sensitivity analysis on a change in the number of input and output items. The efficiency scores of the combination of A1 and A2 with B1 and B2 in Table 4 are shown in Figure 2.

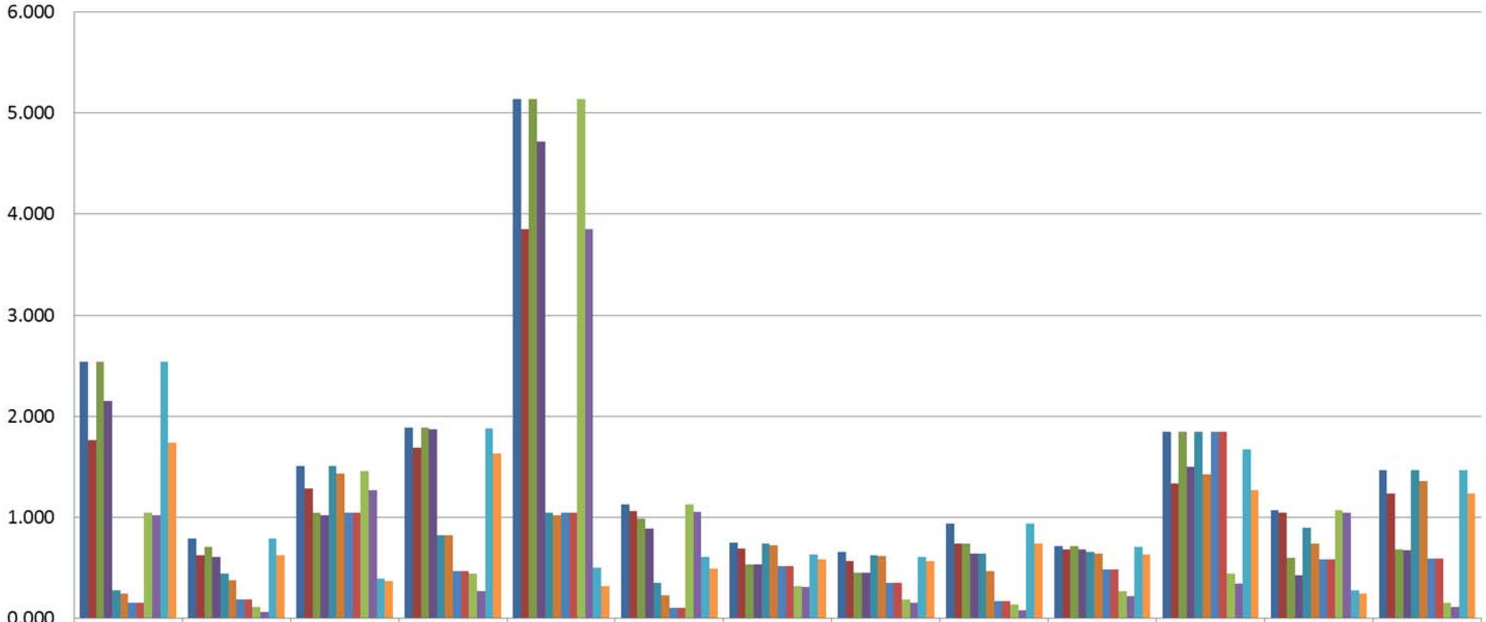
From Figure 2, we notice that Kuala Lumpur and Bangkok are relatively high-scoring super cites, but their efficiency score in the case of 2I (eli R&D)-2O and 1I (eli CI and R&D)-2O appears to decrease significantly. Especially, Bangkok was even assessed in these cases as an inefficient city. In contrast, the results from Fukuoka and Sydney appear to yield stable and robust scores. From these findings, we can also compute the average scores and the number of times a city is considered to be a Super-Efficient DMU (i.e., number of times with a score above 1.0), as shown in Figure 3.



	Kuala Lumpur	Sydney	Bangkok	Hong Kong	Fukuoka	Tokyo	Taipei	Mumbai	Singapore	Osaka	Shanghai	Seoul	Beijing
Ave Score	2.736	1.436	1.350	1.180	1.115	0.922	0.717	0.679	0.575	0.571	0.534	0.468	0.460
Number of times as SE	10	10	8	6	10	6	4	4	0	0	0	0	0

Figure 2. Average score and number of times as a Super-Efficient DMU in the information elimination case

If we compare Figure 3 (as a comparative target), we observe that Sydney ranks on the second place, while the number of times it qualifies as an SE city is even 10. In contrast, Bangkok and Hong Kong have a lower rank, viz. the third and fourth place, while the number of times as an SE is also lower, viz. 8 and 6, respectively. We also notice that the rank order for inefficient cities is also significantly changing; especially Beijing appears to shift downward dramatically to the 13th position.



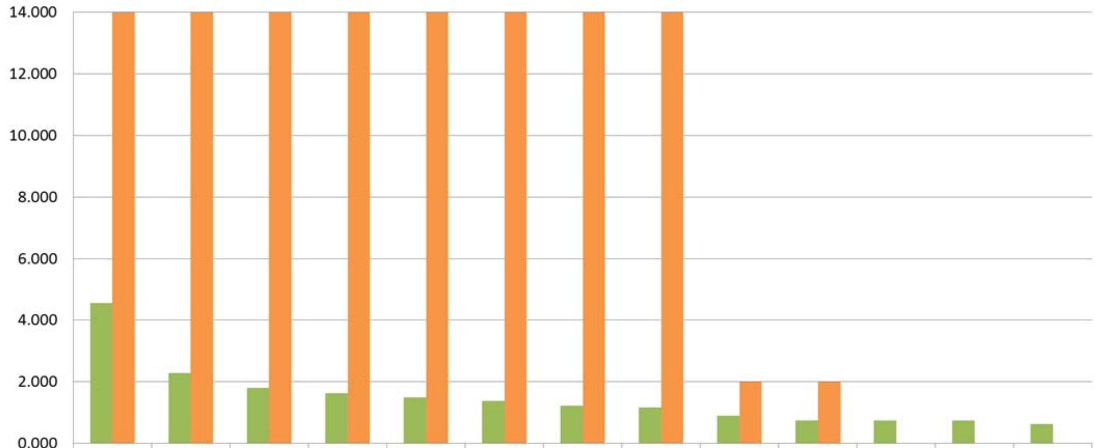
	Bangkok	Beijing	Fukuoka	Hong Kong	Kuala Lumpur	Mumbai	Osaka	Seoul	Shanghai	Singapore	Sydney	Taipei	Tokyo
SE-CCR-3I-2O	2.541	0.793	1.509	1.884	5.140	1.126	0.746	0.659	0.940	0.718	1.846	1.075	1.467
SE-SBM-3I-2O	1.767	0.625	1.287	1.691	3.852	1.064	0.690	0.570	0.740	0.682	1.332	1.049	1.239
SE-CCR-2I(Eli-CI)-2O	2.541	0.706	1.044	1.884	5.140	0.986	0.534	0.454	0.742	0.713	1.846	0.598	0.686
SE-SBM-2I(Eli-CI)-2O	2.150	0.609	1.022	1.874	4.721	0.892	0.532	0.454	0.638	0.687	1.498	0.424	0.677
SE-CCR-2I(Eli-R&D)-2O	0.282	0.448	1.509	0.824	1.049	0.357	0.739	0.626	0.642	0.659	1.846	0.896	1.467
SE-SBM-2I(Eli-R&D)-2O	0.249	0.380	1.431	0.821	1.025	0.232	0.726	0.622	0.465	0.642	1.423	0.745	1.358
SE-CCR-1I(Eli-CI, R&D)-2O	0.158	0.186	1.044	0.472	1.049	0.103	0.520	0.350	0.172	0.483	1.846	0.587	0.597
SE-SBM-1I(Eli-CI, R&D)-2O	0.158	0.186	1.044	0.472	1.049	0.103	0.520	0.350	0.172	0.483	1.846	0.587	0.597
SE-CCR-3I-1O(Eli-GDP)	1.046	0.111	1.462	0.445	5.140	1.126	0.319	0.191	0.142	0.268	0.448	1.075	0.157
SE-SBM-3I-1O(Eli-GDP)	1.018	0.062	1.267	0.275	3.852	1.053	0.311	0.153	0.079	0.221	0.349	1.049	0.112
SE-CCR-3I-1O(Eli-Env)	2.541	0.793	0.398	1.876	0.499	0.611	0.632	0.613	0.940	0.709	1.675	0.279	1.467
SE-SBM-3I-1O(Eli-Env)	1.743	0.625	0.367	1.634	0.320	0.493	0.584	0.570	0.740	0.637	1.272	0.245	1.239

Figure 3. Sensitivity analysis results of a change in the number of input and output items

4.3.2 Sensitivity analysis for efficient DMUs elimination case

We will now also carry out a sensitivity analysis on the efficient DMUs elimination case. The efficiency scores of the combination of A1 and A2 with B3 in Table 4 are shown in Figure 4.

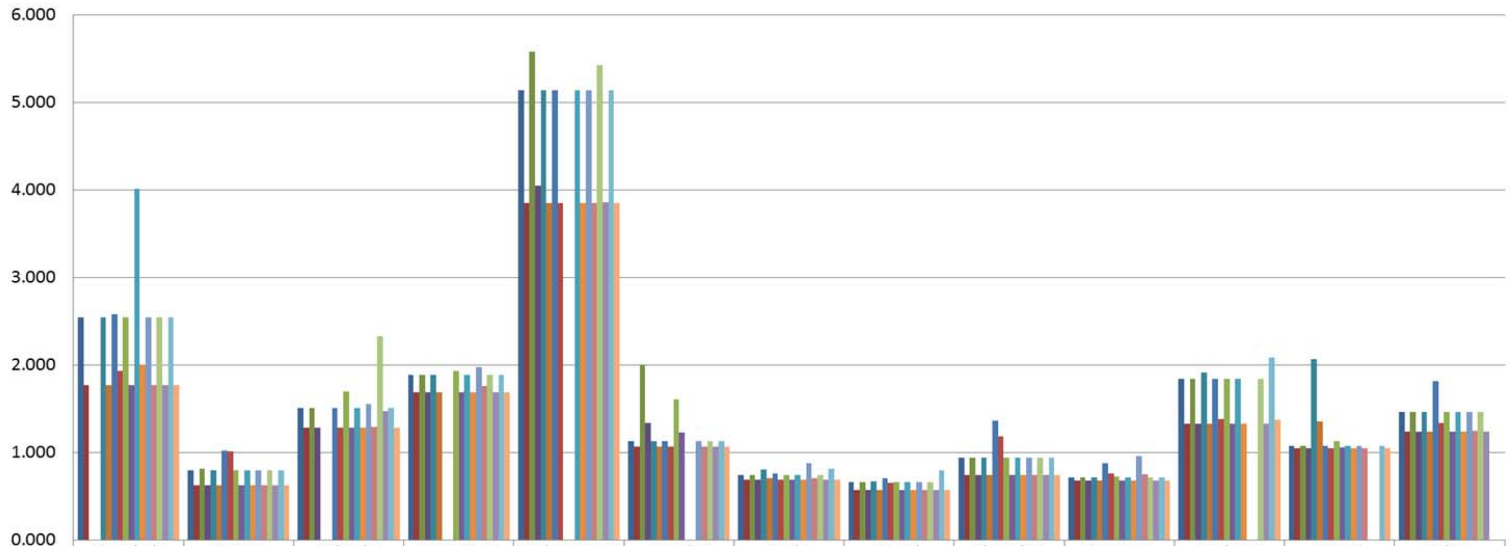
In Figure 4, we notice that the results were not dramatically changing. If we compute the average scores and the number of times a city is a Super-Efficient DMU (i.e. number of times above score 1.0, as shown in Figure 5), we find interesting absolute shifts, but still similar patterns.



	Kuala Lumpur	Bangkok	Hong Kong	Sydney	Fukuoka	Tokyo	Mumbai	Taipei	Shanghai	Beijing	Osaka	Singapore	Seoul
Ave Score	4.562	2.291	1.803	1.618	1.486	1.385	1.223	1.160	0.894	0.749	0.737	0.735	0.632
Number of times as SE	14	14	14	14	14	14	14	14	2	2	0	0	0

Figure 4. Average score and number of times as Super-Efficient DMU in a DMUs elimination case

If we compare Figure 5 with Figure 1 (as a comparative benchmark), then we notice that all rank orders of scores in Figure 1 and Figure 5 offer completely the same results. We also notice that Shanghai and Beijing are two times evaluated as a super-efficient city. From Figure 4, it can be seen that these results are both showing up for the case with the elimination of Hong Kong. This result suggests that cities in China may have similar characteristics and thus may likely have a great influence on each other.



	Bangkok	Beijing	Fukuoka	Hong Kong	Kuala Lumpur	Mumbai	Osaka	Seoul	Shanghai	Singapore	Sydney	Taipei	Tokyo
SE-CCR-3I-2O-13DMUs	2.541	0.793	1.509	1.884	5.140	1.126	0.746	0.659	0.940	0.718	1.846	1.075	1.467
SE-SBM-3I-2O-13DMUs	1.767	0.625	1.287	1.691	3.852	1.064	0.690	0.570	0.740	0.682	1.332	1.049	1.239
SE-CCR-eli-BAN		0.813	1.509	1.884	5.581	2.003	0.746	0.659	0.940	0.718	1.846	1.075	1.467
SE-SBM-eli-BAN		0.625	1.287	1.691	4.046	1.334	0.690	0.570	0.740	0.682	1.332	1.049	1.239
SE-CCR-eli-FUK	2.541	0.793		1.884	5.140	1.126	0.807	0.669	0.940	0.720	1.911	2.069	1.467
SE-SBM-eli-FUK	1.767	0.625		1.691	3.852	1.064	0.711	0.570	0.740	0.682	1.332	1.356	1.239
SE-CCR-eli-HON	2.582	1.021	1.509		5.140	1.126	0.757	0.708	1.362	0.882	1.846	1.075	1.818
SE-SBM-eli-HON	1.930	1.011	1.287		3.852	1.064	0.691	0.654	1.180	0.764	1.386	1.049	1.334
SE-CCR-eli-KUA	2.541	0.793	1.695	1.930		1.609	0.746	0.659	0.940	0.722	1.846	1.132	1.467
SE-SBM-eli-KUA	1.768	0.625	1.287	1.691		1.228	0.690	0.570	0.740	0.684	1.333	1.062	1.239
SE-CCR-eli-MUM	4.016	0.793	1.509	1.884	5.140		0.746	0.659	0.940	0.718	1.846	1.075	1.467
SE-SBM-eli-MUM	2.005	0.625	1.287	1.691	3.852		0.690	0.570	0.740	0.682	1.332	1.049	1.239
SE-CCR-eli-SYD	2.541	0.793	1.550	1.977	5.140	1.126	0.882	0.659	0.940	0.960		1.075	1.467
SE-SBM-eli-SYD	1.767	0.625	1.293	1.765	3.852	1.064	0.705	0.570	0.740	0.753		1.049	1.243
SE-CCR-eli-TAI	2.541	0.793	2.327	1.884	5.424	1.126	0.746	0.659	0.940	0.718	1.846		1.467
SE-SBM-eli-TAI	1.767	0.625	1.471	1.691	3.861	1.064	0.690	0.570	0.740	0.682	1.332		1.239
SE-CCR-eli-TOK	2.541	0.793	1.509	1.884	5.140	1.126	0.811	0.799	0.942	0.718	2.083	1.075	
SE-SBM-eli-TOK	1.767	0.625	1.287	1.691	3.852	1.064	0.690	0.570	0.740	0.682	1.375	1.049	

Figure 5. Sensitivity analysis results for efficient DMUs eliminated

5. Conclusions and Lessons

DEA is a quantitative method for assessing the efficiency of economic agents, such as cities. It has found various applications in a variety urban benchmark studies. It is an important question whether different DEA methods and different DEA information levels lead to different results.

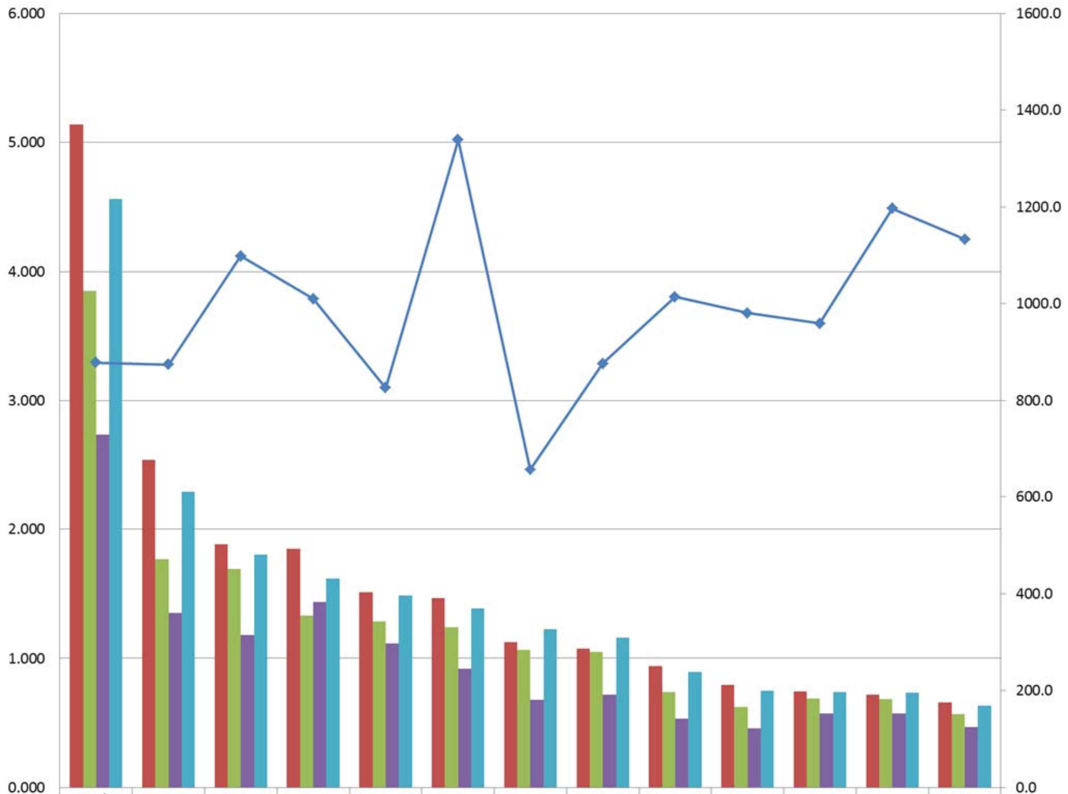
In this paper, we have tested the robustness of DEA results – applied to the performance of various Asian-Pacific cities (13 in total) – against variations in the number of outputs, the number of inputs, the number of actors and the type of DEA-model used.

From our efficiency evaluation results for 13 Asian-Pacific cities based on the SE-CCR model and the SE-SBM model using a 3Input-2Output information base, Kuala Lumpur, Bangkok, Hong Kong, Sydney, Fukuoka, Tokyo, Mumbai and Taipei may be regarded as super-efficient cities. In contrast, Shanghai, Beijing, Osaka, Singapore and Seoul are regarded as inefficient cities.

Most comparative studies including the GPCI-2016 scores 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 Asia-Pacific cities, using a comparative data set. The research presented in the present study has offered interesting insights into the benchmark position of Asia-Pacific cities, based on an extensive data set. Our findings reveal striking differences compared to standard ranking and benchmarking procedures (GPCI-2016), as shown in Figure 6. In conclusion, our method to calculate at unambiguous DEA ranking results provides promising findings leading to further research on urban performance analysis.

In our empirical analysis, we carried out a sensitivity analysis in two steps, viz. (A) a methodological comparison, and (B) a sensitivity check on the number of input items and output items, and the number of DMUs. From these results, it appeared that significant changes in efficiency scores may occur in the case of shifts in the number of input and output items. From these findings, we may draw the conclusion that if an important item (either input or output) is eliminated, then the efficiency score of all cities may change significantly. The research lesson from this experiment is that we need to carefully select the input and output items in any DEA benchmark analysis.

It seems a logical lesson from our analysis not to be dependent on a few selective input or output criteria in a comparative DEA, but to go for a comprehensive data base. This multi-dimensional information system may next be reduced by means of multivariate statistical techniques (e.g., principal component analysis), so that a more stable and orthogonal data base may be created that is more robust vis-à-vis changes in the underlying multi-dimensional data base.



	Kuala Lumpur	Bangkok	Hong Kong	Sydney	Fukuoka	Tokyo	Mumbai	Taipei	Shanghai	Beijing	Osaka	Singapore	Seoul
SE-CCR-3I-2O	5.140	2.541	1.884	1.846	1.509	1.467	1.126	1.075	0.940	0.793	0.746	0.718	0.659
SE-SBM-3I-2O	3.852	1.767	1.691	1.332	1.287	1.239	1.064	1.049	0.740	0.625	0.690	0.682	0.570
Ave Score (eli I,O items)	2.736	1.350	1.180	1.436	1.115	0.922	0.679	0.717	0.534	0.460	0.571	0.575	0.468
Ave Score (eli DMUs)	4.562	2.291	1.803	1.618	1.486	1.385	1.223	1.160	0.894	0.749	0.737	0.735	0.632
GPCI-2016	878.7	874.3	1098.5	1009.9	826.4	1338.5	657.3	876.3	1014.4	981.0	959.1	1197.0	1133.3

Figure 6. Score comparison between GPCI-2016 and DEA results

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