Multidimensional quality-of-life measure with an application to *Fortune’s* best cities

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Abstract

The notion of the quality of life is about a finite set of measurable attributes that can be weighted by some metric. The quality of life has subjective as well as objective dimensions. Single dimension measures now are recognized as too narrow to fully capture differences in the quality of life. Based upon data envelopment analysis (DEA), the current paper demonstrates how to develop a multidimensional measure to characterize the quality of life and identify its best-practice frontier which balances work and family life and judges practical comfort. Benchmarks are introduced into DEA models to implicitly reflect tradeoff information on quality-of-life related factors and to incorporate evaluation standards. A method is proposed to determine the unique best quality-of-life scale target. Critical quality-of-life factors are identified in a multidimensional construct. *Fortune* magazine’s choice of the 20 best cities—15 domestic and five international—is investigated. © 2001 Elsevier Science Ltd. All rights reserved.

Keywords: Data envelopment analysis; Quality of life; Multidimensional

1. Introduction

As mentioned in Slottje et al. [1], ‘quality-of-life’ like ‘well being’ or ‘social welfare’, has a subjective or normative meaning. A typical measure of quality of life (QOL) considers a finite set of measurable and objective attributes (factors) that can be weighted by some metric. It has been recognized that single dimension measures such as per capita GNP are too narrow to fully capture differences in the QOL. Also, since these attributes have complicated and often indiscernible relationships with each other, multiple attributes are always necessary. Darton [2] was the first to suggest using a multidimensional approach to the issue of economic well being. The multiple attributes must be weighted in some objective and rational way in order to obtain an overall QOL.
index. However, weighting the attributes of QOL can be problematical, since we cannot know how individuals or groups weight the attributes of QOL from which they derive utility. In the past, measures of the QOL have been very narrowly constructed and have suffered from an assumption that the attributes are equally valued by assigning equal weights in practice. In some recent studies (e.g., [3]), among the feasible set of weighting schema, principal components and hedonic or instrumental variables estimating techniques have served as objective and rational ones. However, the weights obtained from these techniques are sometimes difficult to interpret.

A rich and very technical literature has been developed on using index numbers for measuring the QOL [4]. Economists working on this problem have attempted (and continue to do so) to construct an ideal QOL index that satisfies a set of pre-determined axioms. Unfortunately, this rigorous research has shown that such an ideal index does not exist and that the construction of one is thus not possible. This leads us to find alternative approaches to construct a QOL measure.

Given the nature of multidimensionality, we intuitively turn to data envelopment analysis (DEA) [5]. As a mathematical programming technique, DEA was originally designed to measure the relative efficiency within not-for-profit organizations where market prices are not available. However, by its ability to model multidimensional relationships among multiple inputs and multiple outputs without an a priori underlying functional form assumption, DEA has also been applied within a wide variety of areas. Some DEA applications are in the area of socio-economic performance, such as city and nation performance [6–8] and state of society evaluation [9]. In particular, using DEA can circumvent the situation when information on how to weight multiple factors is not clear or even unknown.

The current paper uses Fortune’s 20 best cities in 1996 [10] to illustrate how DEA can be used to measure the QOL. In addition to Fortune’s ranking, new DEA approaches are proposed to capture the difference in QOL among Fortune’s best cities. For example, the returns to scale (RTS) method in DEA is employed to locate a city’s QOL status in a multidimensional construct and to determine the unique best QOL scale target. Benchmarks are introduced into the DEA model to (i) implicitly reflect factor tradeoff information and (ii) incorporate evaluation standards. The critical attributes related to the QOL are identified for each city.

The reminder of the paper is organized as follows. The next section provides a set of factors used by Fortune magazine [10] in selecting the best cities. DEA inputs and outputs are developed from these factors. Basic DEA models are provided for the development of new (DEA) methods and models. These new methods are used to measure the QOL of 15 domestic and five international cities. The QOL of the five international cities is then compared to the best practice of the 15 domestic cities. Conclusions are provided in the last section.

2. Multidimensional quality-of-life measure

We use the data of 15 US domestic cities and five international cities in an illustrative example to demonstrate how DEA can be employed to measure QOL in a multidimensional construct, and to provide additional information regarding the QOL. Table 1 reports 13 factors (attributes) used by Fortune magazine [10] in selecting its best cities. These factors measure aspects of the cost of
Table 1

Fortune’s best cities

<table>
<thead>
<tr>
<th>Rank</th>
<th>City</th>
<th>1996 pop. in millions</th>
<th>Median house income ($)</th>
<th>% of pop. with bachelor’s degree</th>
<th>High-end housing price ($)</th>
<th>Lower-end housing rental ($)</th>
<th>Loaf of French bread ($)</th>
<th>Martini ($)</th>
<th>Class A office rental ($/ft²)</th>
<th>Number of art museums</th>
<th>Number of public libraries</th>
<th>Number of 18-hole golf courses</th>
<th>Violent crime rate per 100,000</th>
<th>Doctors per 1000</th>
</tr>
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<tbody>
<tr>
<td>1</td>
<td>Seattle</td>
<td>2.2</td>
<td>46,928</td>
<td>29.70</td>
<td>586,000</td>
<td>581</td>
<td>1.45</td>
<td>4.50</td>
<td>21</td>
<td>7</td>
<td>117</td>
<td>22</td>
<td>542.3</td>
<td>4.49</td>
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<tr>
<td>2</td>
<td>Denver</td>
<td>1.9</td>
<td>42,879</td>
<td>29.10</td>
<td>475,000</td>
<td>558</td>
<td>0.97</td>
<td>4.00</td>
<td>14</td>
<td>5</td>
<td>60</td>
<td>71</td>
<td>595.6</td>
<td>2.79</td>
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<td>43,576</td>
<td>22.70</td>
<td>299,000</td>
<td>609</td>
<td>1.70</td>
<td>4.00</td>
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<td>6</td>
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<td>125</td>
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<td>318,000</td>
<td>613</td>
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<td>4.50</td>
<td>18</td>
<td>7</td>
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<td>625</td>
<td>1.29</td>
<td>3.75</td>
<td>33</td>
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<td>148</td>
<td>105</td>
<td>714.5</td>
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<td>4.6</td>
<td>54,291</td>
<td>37.30</td>
<td>347,000</td>
<td>535</td>
<td>0.99</td>
<td>3.75</td>
<td>17</td>
<td>8</td>
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<tr>
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<td>650</td>
<td>1.50</td>
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<td>600,000</td>
<td>740</td>
<td>1.19</td>
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<td>775</td>
<td>0.99</td>
<td>3.99</td>
<td>18</td>
<td>8</td>
<td>102</td>
<td>45</td>
<td>1296.30</td>
<td>4.02</td>
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<td>351,000</td>
<td>888</td>
<td>1.09</td>
<td>4.25</td>
<td>34</td>
<td>25</td>
<td>240</td>
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<td>1.53</td>
<td>3.50</td>
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<td>695</td>
<td>1.19</td>
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<td>26</td>
<td>4</td>
<td>37</td>
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<td>591</td>
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<td>3.60</td>
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<td>90</td>
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<td>122</td>
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<td>17.80</td>
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<td>591</td>
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<td>90</td>
<td>178</td>
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<td>15</td>
<td>61</td>
<td>4</td>
<td>156.3</td>
<td>1.26</td>
</tr>
</tbody>
</table>

^a Per capita income.
^b Percent of population 25 and older with post-secondary education.
^c Total museums and galleries.
^d NA: not available.
living, demographics, business, and leisure. On the basis of these factors, we developed six DEA inputs and six DEA outputs as follows. As in [9], DEA inputs represent negative evaluation items (smaller values are better and more desirable) while DEA outputs represent positive evaluation items (greater values are preferred).

**DEA inputs**

- $x_1 =$ high-end housing price (1000 US$);
- $x_2 =$ lower-end housing monthly rental (US$);
- $x_3 =$ cost of a loaf of French bread (US$);
- $x_4 =$ cost of martini (US$);
- $x_5 =$ Class A office rental (US$/ft^2);
- $x_6 =$ number of violent crimes.

**DEA outputs**

- $y_1 =$ median household income (US$);
- $y_2 =$ number of population with bachelor’s degree (millions);
- $y_3 =$ number of doctors (thousands);
- $y_4 =$ number of museums;
- $y_5 =$ number of libraries;
- $y_6 =$ number of 18-hole golf courses.

We first present a set of basic DEA models upon which new methods are developed in the current study. Charnes et al. (CCR) [5] proposed the following DEA model:

$$\begin{align*}
&\min \theta_o - \varepsilon \left( \sum_{i=1}^{m} s^-_i + \sum_{r=1}^{s} s^+_r \right) \\
&\text{s.t.} \quad \sum_{j=1}^{n} \lambda_j x_{ij} + s^-_i = \theta_o x_{io}, \quad i = 1, 2, \ldots, m, \\
&\quad \sum_{j=1}^{n} \lambda_j y_{ij} - s^+_r = y_{ro}, \quad r = 1, 2, \ldots, s, \\
&\quad \lambda_j \geq 0, \quad j = 1, \ldots, n,
\end{align*}$$

(1)

where $x_{io}$ and $y_{ro}$ are, respectively, the $i$th input and $r$th output for a city—DMU $o$ (decision-making unit $o$)—under evaluation. The presence of the non-Archimedean $\varepsilon$ in the objective function of (1) effectively allows the minimization over $\theta_o$ to preempt the optimization involving the slacks $s^-_i$ and $s^+_r$. Thus, the optimization can be computed in a two-stage process with maximal proportional reduction of inputs being achieved first, via the optimal $\theta^*_o$; then, in the second stage, movement onto the efficient frontier is achieved via the slack variables.

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1See the November 1996 issue of *Fortune* [10] for other factors used in selecting the best cities, e.g., climate. The current study does not include climate, since it is uncontrollable by the cities.

2For example, $y_2$ (number of population with bachelor’s degree) is developed from the city population and the percentage of population with a bachelor’s degree. Note that some factors’ units were changed.
Since the efficient frontier determined by (1) exhibits constant returns to scale (CRS), we call model (1) the CRS (DEA) model. A DMU is said to be CRS efficient if and only if (a) $y^*_o = 1$, and (b) all optimum slack values ($s_i^-$, $s_i^+$) are zero. If a city under evaluation satisfies these two conditions, it represents the best practice or is on the QOL frontier. In DEA, $y^*_o$ is called the efficiency score. In the current study, $y^*_o$ represents the QOL score.

The dual linear program to (1) is

$$\begin{align*}
\text{max} & \sum_{r=1}^{s} u_r y_{ro} \\
\text{s.t.} & \quad \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{s} v_i x_{ij} \leq 0, \quad j = 1, \ldots, n, \\
& \quad \sum_{i=1}^{m} v_i x_{io} = 1, \\
& \quad u_r, v_i \geq 0.
\end{align*}$$

If we impose an additional convexity constraint of $\sum_{j=1}^{n} \lambda_j = 1$ into the CRS model (1), the resulting frontier exhibits variable returns to scale (VRS). We here name it the VRS (DEA) model [11]:

$$\begin{align*}
\text{min} b_o - \varepsilon \left( \sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right) \\
\text{s.t.} & \quad \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = b_o x_{io}, \quad i = 1, 2, \ldots, m, \\
& \quad \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro}, \quad r = 1, 2, \ldots, s, \\
& \quad \sum_{j=1}^{n} \lambda_j = 1, \\
& \quad \lambda_j \geq 0, \quad j = 1, \ldots, n.
\end{align*}$$

In the current study, multiple attributes related to the QOL are considered in forms of DEA inputs/outputs. As a result, these various attributes are integrated and balanced by DEA-based measures. Instead of (subjectively) combining each single attribute ratio $y_r/x_i$, DEA provides a single virtual output to virtual input ratio, e.g., $\sum_{r=1}^{s} u_r y_r / \sum_{i=1}^{m} v_i x_i$ via linear programming optimization on weights $u_r (r = 1, \ldots, s)$ and $v_i (i = 1, \ldots, m)$.

### 3. Measuring the quality of life across cities

This section demonstrates how DEA models (e.g., models (1) and (2)) can be employed and modified to characterize the QOL across cities. The discussion is carried out via five studies: (i) a method is proposed to integrate inefficiency represented by non-zero slack values into QOL scores.
so that the QOL gap with respect to the best practice can be measured; (ii) an RTS estimation method [12] is utilized to identify a city’s QOL status in a multiple dimensional space, and to uniquely determine the best QOL scale; (iii) benchmarks (standards) are introduced into model (2), and are fixed as components of the QOL frontier for each domestic city under evaluation; (iv) a method is proposed to identify critical attributes with respect to the QOL; and (v) a DEA-based benchmarking model is used to measure the QOL of international cities where the best practice of domestic cities is given and used as a benchmark set. Each international city under evaluation can choose a proper subset of such a benchmark set as the evaluation standard.

3.1. Quality-of-life rating and the identification of benchmarks

Note that $\theta_o^*$ measures QOL in terms of proportional reduction in all inputs of DMU$_o$ when outputs are fixed at their current levels, i.e., $\theta_o^*$ is a radial (proportional) measure of QOL. Non-zero slack values may present in model (1) after the proportional change of $\theta_o^*$. In particular, as indicated in [13,14], slacks may be associated with congestion. Therefore, it is important to integrate non-zero slacks into the $\theta_o^*$.

Although we can use

$$\theta_o^* - \varepsilon \left( \sum_{i=1}^{m} s_i^{--*} + \sum_{r=1}^{s} s_r^{++*} \right)$$


to adjust the results obtained from $\theta_o^*$, the magnitude of $\varepsilon$ may affect the final results. Sueyoshi et al. [15] used the following formula to adjust the $\theta_o^*$:

$$\theta_o^* - \left[ \left( \sum_{i=1}^{m} s_i^{--*} / \text{MR}_i^x \right) + \left( \sum_{r=1}^{s} s_r^{++*} / \text{MR}_r^y \right) \right] / (m + s), \quad (3)$$

where $\text{MR}_i^x = \max_j x_{ij} (i = 1, \ldots , m)$ and $\text{MR}_r^y = \max_j y_{rj} (r = 1, \ldots , s)$. Alternatively, we could use the additive DEA model based upon slacks. However, as shown by Seiford and Zhu [16], DEA models in a form of sum of slacks (e.g., additive model) are equivalent to non-radial DEA models. Further, as pointed out by Cooper et al. [17], the resulting score yields a value that cannot be readily understood and used in management or economics, i.e., the results in (3) are difficult to explain.

The current paper uses the following index as a slack-adjusted QOL measure:

$$\theta_o^* - \frac{1}{m} \left( \sum_{i=1}^{m} s_i^{--*} / x_{io} \right). \quad (4)$$

The rationale for (4) is as follows. As pointed out in [17], $1 - \theta_o^*$ provides a measure of ‘purely technical’ inefficiency while $1/m \left( \sum_{i=1}^{m} s_i^{--*} / x_{io} \right)$ represents ‘average of input-mix’ inefficiency.

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3 Note that output slacks are ignored in (4). Otherwise, we run into the same problem as in (3). Since DEA model (1) measures input efficiency while outputs are fixed at their current levels, it is acceptable that here we only adjust the radial score by input slacks.
Thus,

\[
1 - \theta_o^* + \frac{1}{m} \left( \sum_{i=1}^{m} s_{i,o}^{-} x_{io} \right) = 1 - \left[ \theta_o^* - \frac{1}{m} \left( \sum_{i=1}^{m} s_{i,o}^{-} x_{io} \right) \right]
\]

provides the total input inefficiency for DMU\(_o\). The total inefficiency in (5) actually measures the (input-oriented) QOL gap between the best practice and the city under evaluation. If DMU\(_o\) represents best practice, then (4) yields a value of 1 or (5) yields a value of zero, indicating zero gap.

Table 2 reports \(\theta_o^*\) and its slack-adjusted values as given by (4). Under the assumption of CRS, four US cities (Cincinnati, Atlanta, Milwaukee, and Nashville) are not on the QOL frontier. Under the assumption of VRS, only two US cities (Atlanta and Nashville) are not on the frontier. All the non-frontier cities have non-zero input slack values. Therefore, we use (4) to adjust the inefficiency given by \(\theta_o^*\). Note that, under CRS, Milwaukee has a better QOL rating than does Cincinnati in terms of \(\theta_o^*\). The adjusted \(\theta_o^*\), however, shows the opposite result. This further indicates the necessity to integrate slacks in order to fully and correctly characterize QOL ratings.

For purposes of benchmarking, it is important to identify such measures for non-frontier cities. We can obtain this type of information via the non-zero optimal lambda values in model (1). Table 3 shows the benchmarks for the four non-frontier cities under CRS. For example, the benchmarks for Cincinnati are St. Louis, Minneapolis, and Pittsburgh.4

3.2. RTS regions, quality-of-life status, and the best quality-of-life scale targets

QOL frontier and ratings, and their benchmarks, show the relative QOL status of a particular city (DMU\(_o\)). However, it is still difficult to locate the position of a city to the frontier in a multidimensional space. Here, we seek help from DEA RTS estimations.5 Fig. 1 portrays six RTS regions on the basis of CRS and VRS frontiers and RTS classifications,6 viz., region ‘1’—IRS (increasing RTS), region ‘2’—CRS, and region ‘3’—DRS (decreasing RTS). Two RTS classifications were assigned to the remaining regions. Region ‘4’ is of IRS (input-oriented) and of CRS (output-oriented), region ‘5’ of CRS (input-oriented) or of DRS (output-oriented), and region ‘6’ of IRS (input-oriented) or of DRS (output-oriented).

It is well known that some DEA RTS methods may fail when DEA models have alternate optima. Since it may be impossible, or at least unreasonable, to generate all possible multiple optima in many real world applications, a number of modifications or extensions of the RTS estimation have been developed to deal with multiple optima. In fact, Zhu and Shen [19] and Seiford and Zhu [12] show the following result related to RTS estimation:

4In DEA, the performance of a convex combination of these three benchmark cities dominates that of Cincinnati.

5Note that the concept of RTS may be ambiguous unless a DMU is on VRS frontier. In the DEA literature, we classify the RTS for VRS-inefficient DMUs by their DEA projections. Also, we note that RTS conditions and evaluations have been confined to models using ‘radial measures’ of relative efficiency. See [18] for the situation where RTS is discussed in the form of ‘additive’ and ‘multiplicative’ models.

6This is due to the fact that DEA models with different orientations may yield different RTS classifications if a DMU is not on the VRS frontier.
(i) if DMU<sub>o</sub> exhibits IRS, then \( \sum_{j=1}^{n} \lambda_j^* < 1 \) for all alternate optima in (1);

(ii) if DMU<sub>o</sub> exhibits DRS, then \( \sum_{j=1}^{n} \lambda_j^* > 1 \) for all alternate optima in (1).

The significance of this finding lies in the fact that the possible alternate optimal lambda values obtained from (1) only affect the estimation of RTS for those DMUs that truly exhibit CRS, and have nothing to do with RTS estimation on those DMUs that truly exhibit IRS or DRS. That is, if a DMU exhibits IRS (or DRS), then \( \sum \lambda_j^* \) must be less (or greater) than one, no matter whether there exist alternate optima of \( \lambda_j \).
On the basis of the above result, we use the modified RTS estimation method of Zhu and Shen [19] to determine the RTS classification since both CRS and VRS DEA models are employed. As a result, we explore RTS in two steps. First, select all cities that have $y^o = b^o$ regardless of the value of $P^*_j$ in (1), where $b^o$ is the efficiency score under the VRS DEA model. These cities should be in the CRS region. Next, use the value of $\sum \lambda_j^*$ (in any model (1) outcome) to determine the RTS for the remaining cities.

The last two columns of Table 2 report the QOL scale classifications under input and output orientations, respectively.

The use of RTS estimation here is not designed to estimate the RTS classification of different cities, but rather to locate a particular non-frontier city in terms of QOL status. For example, Cincinnati and Milwaukee are both on the VRS frontier and in RTS region ‘3’. Atlanta and Nashville are in RTS region ‘6’. No cities are in RTS regions ‘1’, ‘2’, ‘4’, and ‘5’.

This type of RTS information also indicates how to improve a city’s QOL to its best scale with less effort. Appa and Yue [20] developed a best RTS model to set targets for non-frontier DMUs. Furthermore, since Appa and Yue’s target corresponds to the largest most productive scale size (MPSS) [21], Zhu [22] proposed using RTS region information to set the same best scale target.

---

7See [12] for a review and discussion of various DEA RTS estimation methods.
i.e., model (1) and the MPSS concept can be used to determine the best scale target for DMU\textsubscript{o}. This involves solving the following linear programming model after solving (1):

\[
\begin{align*}
\min & \quad \sum_{j=1}^{n} \lambda_j - \varepsilon \left( \sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right) \\
\text{s.t.} & \quad \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta^* x_{io}, \quad i = 1, 2, \ldots, m, \\
& \quad \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro}, \quad r = 1, 2, \ldots, s, \\
& \quad \lambda_j, s_i^-, s_r^+ \geq 0.
\end{align*}
\] (6)

On the basis of optimal values from (6) (i.e., \(s_i^-, s_r^+, \text{ and } \sum \lambda_j^*\)), the MPSS concept yields the following best scale target for DMU\textsubscript{o} corresponding to the largest MPSS:

\[
\text{MPSS}_{\text{max}} : \begin{cases} \\
\hat{x}_{io} = (\theta_o^* x_{io} - s_i^-)/\sum \lambda_j^* , \\
\hat{y}_{ro} = (y_{ro} + s_r^+)/\sum \lambda_j^* ,
\end{cases}
\] (7)

where (\(\sim\)) represents the target value and \(s_i^-, s_r^+, \text{ and } \sum \lambda_j^*\) are optimal values from model (6) and \(\theta_o^*\) is the optimal value of \(\theta_o\) in (1).

\(\text{MPSS}_{\text{max}}\) is uniquely determined by \(\theta_o^*\) and \(\sum \lambda_j^*\), since \(\theta_o^*\) and \(\sum \lambda_j^*\) are the unique optimal values in (1) and (6). Note that all the models previously developed are input-oriented. However, by using the relationship between an input-oriented CRS model and an output-oriented CRS model, it is straightforward to show that \(\text{MPSS}_{\text{max}}\) remains the same under both orientations, i.e., the best scale target is uniquely determined and is independent of the DEA model’s orientation.

Table 4 reports the results from (7) for four non-frontier cities with both target and original input and output levels. The differences between the target and original levels are also reported. For example, in order to achieve its best QOL scale, Cincinnati would need to decrease its high-end housing price by 34\% along with other changes. As stated in Fortune [10], the main attraction for families in Cincinnati is the low-stress atmosphere and low cost of living. Also, crime is a lesser worry than in other comparably sized cities. Cincinnati almost achieved its best input scale, particularly in terms of its input of crime. However, given the input levels, big increases in the number of doctors and museums were expected.

Note that the output-orientation RTS classification yields DRS for all the cities in terms of QOL. Importantly, the largest MPSS would be appropriate for the DRS cities. However, Atlanta and Nashville are classified as IRS cities by the input-oriented DEA model. In this case, the smallest MPSS would be appropriate. We can obtain the corresponding best scale targets by changing the objective of (6) to maximization. In our case, the smallest best RTS targets for Atlanta and Nashville are the same as the largest ones. We therefore have unique best QOL scale targets for non-frontier cities.
Table 4
Best quality-of-life scale targets

<table>
<thead>
<tr>
<th>Non-frontier city</th>
<th>Cincinnati</th>
<th>Atlanta</th>
<th>Milwaukee</th>
<th>Nashville</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Original</td>
<td>Target</td>
<td>Change a (%)</td>
<td>Original</td>
</tr>
<tr>
<td>Housing price</td>
<td>467</td>
<td>308</td>
<td>-34</td>
<td>600</td>
</tr>
<tr>
<td>Housing rental</td>
<td>580</td>
<td>551</td>
<td>-5</td>
<td>740</td>
</tr>
<tr>
<td>Cost of French bread</td>
<td>1.25</td>
<td>0.98</td>
<td>-22</td>
<td>1.19</td>
</tr>
<tr>
<td>Cost of martini</td>
<td>3.75</td>
<td>3.44</td>
<td>-8</td>
<td>6.75</td>
</tr>
<tr>
<td>Cost of office rental</td>
<td>20</td>
<td>18</td>
<td>-10</td>
<td>20</td>
</tr>
<tr>
<td>Violent crime</td>
<td>882.40</td>
<td>837.95</td>
<td>-5</td>
<td>2963.10</td>
</tr>
<tr>
<td>Household income</td>
<td>38,455</td>
<td>37,379</td>
<td>-3</td>
<td>43,249</td>
</tr>
<tr>
<td>Bachelor’s degree</td>
<td>0.32</td>
<td>0.50</td>
<td>56</td>
<td>0.92</td>
</tr>
<tr>
<td>Number of doctors</td>
<td>4.48</td>
<td>9</td>
<td>101</td>
<td>8</td>
</tr>
<tr>
<td>Number of museums</td>
<td>4</td>
<td>9</td>
<td>125</td>
<td>9</td>
</tr>
<tr>
<td>Number of libraries</td>
<td>71</td>
<td>116</td>
<td>63</td>
<td>118</td>
</tr>
<tr>
<td>Number of golf courses</td>
<td>94</td>
<td>91</td>
<td>-3</td>
<td>102</td>
</tr>
</tbody>
</table>

min \sum z_i = 1.02879 0.95526 1.06775 0.96919

*A negative sign indicates a decrease and a positive sign indicates an increase in the original value.*
3.3. Incorporation of benchmarks and value judgments

The above analyses reflect the natural structure of the data set. However, as we can see, 75% of the US domestic cities studied represent best-practice QOL. It has been recognized that this is caused by (a) excessive inputs and outputs, and (b) the weight flexibility in model (2). Numerous methods have been proposed to reduce the number of frontier DMUs if this is seen as necessary. For example, we may (i) incorporate some weight restrictions, such as cone-ratios or assurance regions [23,24] in model (2), or (ii) use the preference structure model of [25] via model (1). Note that these methods require additional explicit information on tradeoffs among inputs and outputs. Unfortunately, the current study does not have access to this type of information.

It might be argued that one could reduce the number of DEA inputs/outputs by using some statistic techniques, e.g., correlation analysis. But, this may affect the comprehensiveness and accuracy of the measure in a sense that not all dimensions are considered even though some may be strongly correlated. Therefore, the current study seeks an alternative way to implicitly express the tradeoff information and further reduce the number of frontier DMUs.

Recall that Fortune magazine ranked Seattle, Denver, and Philadelphia as the top three best cities in balancing work and family life [10]. Their list of best cities was created by incorporating the results of Arthur Andersen’s work with information and analyses supplied by writers and researchers worldwide. The top three best cities thus implicitly reflect experts’ opinions/information on input/output tradeoffs.

Recall also that for a city under evaluation, model (2) determines a set of referent frontier cities which are represented by a set of binding constraints. These frontier cities actually form the benchmark set for a particular city under evaluation. The tradeoff information is represented by the efficient facets constructed from these cities. Setting (fixing) the top three Fortune cities as benchmarks in our DEA analysis can therefore implicitly express tradeoff information. We proceed as follows.

Let \( B = \{ \text{DMU}_j : j \in I_B \} \) be the benchmark set. In this case, \( B = \{ \text{Seattle, Denver, Philadelphia} \} \). We then modify model (2) to the following linear programming model:

\[
\begin{align*}
\max & \quad \sum_{r=1}^{s} u_r y_{ro} \\
\text{s.t.} & \quad \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} = 0, \quad j \in I_B, \\
& \quad \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \quad j \notin I_B, \\
& \quad \sum_{i=1}^{m} v_i x_{io} = 1, \\
& \quad u_r, v_i \geq 0.
\end{align*}
\]
By applying equalities in the constraints associated with benchmark DMUs, model (8) measures DMU_o’s QOL against a reference set containing B, i.e., the top three cities must be used in constructing the efficient facets in evaluating DMU_o. The equality constraints associated with set B implicitly represent tradeoffs among various inputs/outputs.

Note that model (8) may be infeasible because (i) the DMUs in set B cannot be fit into the same facet when they number greater than \( m + s - 1 \), where \( m \) is the number of inputs and \( s \) is the number of outputs, and (ii) the DMUs in set B construct an inefficient (dominated) facet. Case (i) can be avoided by selecting benchmark DMUs such that the number of selected DMUs is less than \( m + s - 1 \). Case (ii) can be circumvented by modifying model (8) into

\[
\begin{align*}
  z^*_o &= \max \sum_{r=1}^s u_r y_{ro} \\
  \text{s.t.} & \sum_{r=1}^s u_r y_{rj} - \sum_{i=1}^m v_i x_{ij} = 0, \quad j \in B, \\
  & \sum_{r=1}^s u_r y_{rj} - \sum_{i=1}^m v_i x_{ij} \leq 0, \quad j \notin B, \quad j \neq o, \\
  & \sum_{i=1}^m v_i x_{io} = 1, \\
  & u_r, v_i \geq 0.
\end{align*}
\]

If DMU_o dominates the DMUs in B (case (ii) and model (8) will be infeasible), we have \( z^*_o > 1 \), where \( z^*_o \) is the optimal value to model (9).

Table 5 reports the results from model (8). Seven cities (Minneapolis, St. Louis, Washington, Pittsburgh and the cities in B, Seattle, Denver, and Philadelphia) are now on the set B-adjusted QOL frontier. Four frontier cities under model (1) (Raleigh-Durham, Dallas-Fort Worth, Baltimore, and Boston) are no longer on the set B-adjusted frontier. The scores for the original four non-CRS frontier cities also dropped. We note that, based upon the scores obtained from model (8), Cincinnati again has a better QOL status than Milwaukee.

We may divide the 15 cities into two groups on the basis of model (8)’s ranking (Table 5): the top nine Fortune cities, and the remaining six cities. In this case, after incorporating the benchmarks, our DEA method provides a very consistent ranking with that of Fortune, although the DEA ranking has ties in Fortune’s top nine cities. This further justifies the DEA results with Fortune’s ranking, and vice versa.

### 3.4. Critical quality-of-life factors

Note that four cities (Cincinnati, Atlanta, Milwaukee, and Nashville) are not on the best QOL frontier, suggesting that every factor is important in reaching the frontier. However, we can use
the following DEA model to determine the minimum change required on each individual input in order to reach the frontier:\(^8\)

\[
\begin{align*}
\min & \quad \theta^k_o \\
\text{s.t.} & \quad \sum_{j=1}^{n} \lambda_j x_{kj} = \theta^k_o x_{ko}, \quad i = k, \\
& \quad \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{io}, \quad i \neq k, \\
& \quad \sum_{j=1}^{n} \lambda_j y_{rij} - s_r^+ = y_{ro}, \quad r = 1, 2, \ldots, s, \\
& \quad \lambda_j \geq 0, \quad j = 1, \ldots, n.
\end{align*}
\]

Let \(\theta^k_o^* = \max_k \{\theta^k_o\}\). Then, this particular \(i\)th input gives the shortest path to the QOL frontier for DMU\(_o\). We thus say that this input is critical for DMU\(_o\)’s QOL. Table 6 reports the critical QOL factors for the four non-frontier cities. Household income appears to be the critical output. Housing rental is the critical input for Cincinnati while housing price is the critical input for Milwaukee.

For efficient cities, critical factors are identified with respect to the following rule: the QOL classification of a city changes if the magnitude of (some) QOL factor(s) changes. Accordingly,

\(^8\)A similar model can be obtained to determine the minimum change required for each individual output in order to reach the frontier.
model (10) is modified as

\[
\begin{align*}
\min & \quad \theta^I_o \\
\text{s.t.} & \quad \sum_{j=1}^{n} \lambda_j x_{ij} = \theta^I_o x_{io}, \quad i \in I, \\
& \quad \sum_{j=1}^{n} \sum_{j \neq o} \lambda_j x_{ij} + s^-_i = x_{io}, \quad i \notin I, \\
& \quad \sum_{j=1}^{n} \sum_{j \neq o} \lambda_j y_{ij} - s^+_r = y_{ro}, \quad r = 1, 2, \ldots, s, \\
& \quad \lambda_j \geq 0, \quad j \neq o,
\end{align*}
\]

(11)

where \( I \) represents the input subset of interest. A similar model can be obtained based upon outputs (see [26]). As indicated in [26], model (11) may be infeasible for some \( I \), where the infeasibility means that input changes associated with set \( I \) across all DMUs do not change the efficiency status of DMU\(_o\). Consequently, here we can use the infeasibility information to identify the critical QOL factors. That is, if model (11) is feasible, then the factors in set \( I \) are important to the QOL of a specific efficient city.

Each input and each output was tested. Also, some combinations of inputs and outputs were considered, including set \( I = \{ \text{cost of living}\} = \{ \text{housing price, housing rental, French bread, Martini} \} \), set \( I = \{ \text{cost of living, business}\} = \{ \text{cost of living, office rental} \} \), and set \( I = \{ \text{leisure}\} = \{ \text{museums, libraries, golf courses} \} \), etc.

Table 6 also reports the critical factors for the best-practice cities. For example, housing rental and household income were found to be the two critical factors in Seattle’s QOL. Note that the median household income for Seattle is almost $47,000, ranking only below Washington, DC and San Francisco. If this output is decreased (along with increases in other cities), Seattle may not be on the QOL frontier anymore, not to mention maintaining its number one ranking.

Cost of living and business office rental together constitute a critical factor for Boston’s QOL. Note that Boston’s cost-of-living index is very highly ranked among the nation’s largest cities.

Finally, we point out that the critical factors found here are such under a ‘relative basis’, since DEA compares performances within a group of cities. If some existing cities were to be excluded or new cities added, corresponding results would likely vary.

3.5. Measuring the quality of life of international cities

Since we now have the QOL frontier of Fortune’s 15 domestic cities, we may compare the QOL of each international city to this existing frontier. Troutt et al. [27] and Seiford and Zhu [28] developed a DEA-based method to determine whether a new case is acceptable compared to the existing standard. As an extension to [28], we use the following linear programming to measure
the QOL for each international city:

\[
\min \theta_{\text{new}}
\]

s.t. \( \sum_{j \in E} \lambda_j x_{ij} + s_i^- = \theta_{\text{new}} x_{i}^{\text{new}}, i = 1, 2, \ldots, m \),

\( \sum_{j \in E} \lambda_j y_{ij} - s_r^+ = y_{r}^{\text{new}}, r = 1, 2, \ldots, s \),

\( \lambda_j \geq 0, j \in E \),

where \( x_{i}^{\text{new}} \) and \( y_{r}^{\text{new}} \) are, respectively, the \( i \)th input and \( r \)th output for a new DMU—an international city.

On the basis of [28–30], and assuming all data are positive, we have (case 1) \( \theta_{\text{new}}^* \geq 1 \) indicating that the performance of this new DMU is at least as good as that of frontier DMUs represented by set \( E \), and (case 2) \( \theta_{\text{new}}^* < 1 \) indicating that the performance of this new DMU is worse than that of frontier DMUs represented by set \( E \).

Model (12) is actually a benchmarking model based upon DEA where DMUs in set \( E \) are incorporated as the benchmarks.

---

**Table 6**

<table>
<thead>
<tr>
<th>Fortune's rank</th>
<th>City</th>
<th>Critical factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Seattle</td>
<td>{housing rental}, {household income}</td>
</tr>
<tr>
<td>2</td>
<td>Denver</td>
<td>{housing price, housing rental, office rental}, {household income}</td>
</tr>
<tr>
<td>3</td>
<td>Philadelphia</td>
<td>{cost of living, business}</td>
</tr>
<tr>
<td>4</td>
<td>Minneapolis</td>
<td>{cost of living, business}</td>
</tr>
<tr>
<td>5</td>
<td>Raleigh-Durham</td>
<td>{household income}, {household income, bachelor’s degree, doctors}</td>
</tr>
<tr>
<td>6</td>
<td>StLouis</td>
<td>{French bread, martini}</td>
</tr>
<tr>
<td>7</td>
<td>Cincinnati</td>
<td>{housing rental}, {household income}</td>
</tr>
<tr>
<td>8</td>
<td>Washington</td>
<td>{cost of living, business}</td>
</tr>
<tr>
<td>9</td>
<td>Pittsburgh</td>
<td>{French bread, martini}, {violent crime}, {leisure}</td>
</tr>
<tr>
<td>10</td>
<td>Dallas-Fort Worth</td>
<td>{housing price, housing rental, office rental}, {office rental}, {bachelor’s degree}, {bachelor’s degree, doctors}</td>
</tr>
<tr>
<td>11</td>
<td>Atlanta</td>
<td>{French bread}, {cost of living, business}</td>
</tr>
<tr>
<td>12</td>
<td>Baltimore</td>
<td>{housing price, housing rental, office rental}, {office rental}, {French bread, martini}, {household income}</td>
</tr>
<tr>
<td>13</td>
<td>Boston</td>
<td>{cost of living, business}</td>
</tr>
<tr>
<td>14</td>
<td>Milwaukee</td>
<td>{housing price}, {cost of living, business}</td>
</tr>
<tr>
<td>15</td>
<td>Nashville</td>
<td>{French bread}, {cost of living, business}</td>
</tr>
</tbody>
</table>

\( ^a \) The critical factors are identified in a different way for the four non-quality-of-life frontiers.

---

9 This model is used in [29,30] to investigate bank branch performance before and after re-engineering.

10 Model (12) is different from the super-efficiency DEA model [31,32]. The difference lies in the fact that in the latter, only the DMU under evaluation is excluded from the reference set. The reference set thus varies for DMUs under evaluation, whereas the reference set is fixed as set \( E \) in model (12).
The dual to (12) is
\[
\begin{align*}
\max & \sum_{r=1}^{s} u_{r} y_{r o}^{\text{new}} \\
\text{s.t.} & \sum_{r=1}^{s} u_{r} y_{r j} - \sum_{i=1}^{s} v_{i} x_{ij} \leq 0, \quad j \in E, \\
& \sum_{i=1}^{m} v_{i} x_{i o}^{\text{new}} = 1, \\
& u_{r}, v_{i} \geq 0.
\end{align*}
\]

The difference between (8) and (13) is that a DMU must select all benchmarks as referent DMUs in (8) whereas a DMU may select a subset of benchmarks in (13).

As pointed out by Ali and Chen [33], super-efficiency DEA models may result in large non-zero input slack values which, sometimes, are even larger than the original input levels.\footnote{In the original DEA model, e.g., (1), the input slack value is always less than its corresponding original input level.} The same situation may also be applied to model (12). For example, consider three DMUs, \( A \), \( B \), and \( C \), with two input and a single output as pictured in Fig. 2. If we set \( E = \{ A, B \} \) and solve (12) for \( C \), we obtain
\[
\theta_{C}^{*} = 1.5, \quad \theta_{B}^{*} = 1, \quad s_{C}^{C^{*}} = 5.5 \text{ and all other variables zero.}
\]

Note that \( s_{C}^{C^{*}} = 5.5 > x_{2C} = 5 \). This is due to the fact that \( C \) is projected onto \( C' \) which is on the extended DEA frontier of the two remaining DMUs \( A \) and \( B \). (DEA frontier is the line segment \( AB \).) However, \( C' \) should be rated as inefficient (among \( A \), \( B \), and \( C' \)) because of the non-zero slack value in its second input. In order to consider the inefficiency represented by non-zero slack values, we establish the following linear programming problem after solving model (12) [33]:
\[
\begin{align*}
\min & \sum_{i=1}^{m} s_{i}^{o} / x_{i o} \\
\text{s.t.} & \sum_{j \in E} \lambda_{j} x_{ij} + s_{i}^{o} = \theta_{\text{new}} x_{i o}, \quad i = 1, 2, \ldots, m, \\
& \sum_{j \in E} \lambda_{j} x_{r j} - s_{r}^{o} = y_{r o}, \quad r = 1, 2, \ldots, s, \\
& \lambda_{j} \geq 0, \quad j \in E,
\end{align*}
\]

where \( \theta_{\text{new}}^{*} \) is the optimal value to (12) and is fixed in (14). Model (14) maximizes the average input slack mix. We now define
\[
\Theta_{\text{new}} = \theta_{\text{new}}^{*} - \frac{1}{m} \left( \sum_{i=1}^{m} \frac{s_{i}^{o} / x_{i o}}{x_{i o}} \right).
\]

Similar to the index defined in (4), \( \Theta_{\text{new}} \) can be used to represent the average performance gap between a unit on the best-practice frontier and \( \text{DMU}_o \). Applying (14) and (15) to point \( C \) in
In Fig. 2, we have

$$
\Theta_C = \theta_C^* - \frac{s_1^{C-} / x_{1C} + s_2^{C-} / x_{2C}}{2} = 1.5 - \frac{0 + 5.5/5}{2} = 1.05.
$$

Table 7 reports the results from models (12) and (15). On the basis of (12), Hong Kong is the only under-performing city compared to the best practice of 15 US cities. However, if we use the slack-adjusted scores, Singapore becomes another under-performing city in terms of US best-practice QOL. Table 7 also provides the average input values of the 15 US cities. Note that Singapore has a very small value on violent crime compared to the average of US cities.\(^{12}\) By proportional change on all inputs in model (12), this small value leads to a large benchmarking score (optimal value to model (12)) with a zero slack on violent crime. As a result, the mechanism of model (15) yields large slack values on the other inputs for Singapore. As a matter of fact, all non-zero slack values are much greater than the original input values. The original benchmarking score is

\(^{12}\)The average violent crime of the 15 US cities is almost 14 times that of Singapore.
Table 7
Quality of life of Fortune’s ‘best’ international cities

<table>
<thead>
<tr>
<th>City</th>
<th>Benchmarking score</th>
<th>Slacks</th>
<th>Original value</th>
<th>Violent crime</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Slack-adjusted</td>
<td>Housing price</td>
<td>Housing rental</td>
<td>Cost of French bread</td>
</tr>
<tr>
<td>Toronto</td>
<td>1.21116</td>
<td>7.26</td>
<td>55.98</td>
<td>0</td>
</tr>
<tr>
<td>London</td>
<td>2.11785</td>
<td>834.61</td>
<td>1537.68</td>
<td>0</td>
</tr>
<tr>
<td>Singapore</td>
<td>2.56065</td>
<td>192.45</td>
<td>5174.92</td>
<td>1.38</td>
</tr>
<tr>
<td>Paris</td>
<td>7.10270</td>
<td>3952.66</td>
<td>6377.09</td>
<td>3.61</td>
</tr>
<tr>
<td>Hong Kong</td>
<td>0.64351</td>
<td>264.31</td>
<td>706.64</td>
<td>0</td>
</tr>
</tbody>
</table>

Average of US cities: 405, 649, 1.22, 4.23, 22, 1843.4

The (number) next to the slack-adjusted score represents rank.
therefore biased by focusing on violent crime only. The slack-adjusted benchmarking score, on the other hand, balances all inputs and yields an improved result.

4. Conclusions

In measuring the QOL of cities, the November 1996 issue of *Fortune* [10] “threw all the information into a database, contacted 650 high-ranking executives, and came up with a list of 20 winning cities”. Obviously, it was a tedious task to develop measures designed to balance numerous factors that contribute to the QOL. This is due to the problems of multidimensionality, as well as to the often unknown relationships among various QOL factors. The current paper showed that by using DEA, one is able to develop a multidimensional QOL measure without a priori knowledge of factor relationships.

Some new DEA developments were used to capture the multidimensionality of QOL and to measure practical comfort for living. It was shown that RTS estimation can be used to determine both QOL status in a multidimensional space as well as the unique best QOL scale. The current study also offers a way to identify critical QOL factors for a given city. Such new information is important in maintaining a best QOL status.

The current paper also provides two new ways to incorporate benchmarks into DEA models, as follows: (1) use all the benchmarks (DMUs) in constructing the efficient facets for each DMU under evaluation. This allows the implicit incorporation of tradeoff information on various QOL factors; and (2) allow each DMU under evaluation to select a subset of benchmarks (DMUs). The latter method is particularly suitable for measuring the QOL of international cities, since each such city is measured against the same best-practice frontier (standard). Since the number of outputs and inputs in the current study was much larger than the number of international cities, only one (Hong Kong) was found inefficient when the standard DEA model (1) was used. Thus, the standard DEA model was unable to discriminate the QOL among international cities. The benchmarking DEA model offers an alternative way to cope with such situations.

Although *Fortune* [10] ranks the 20 best cities, our intention was simply to provide in-depth information on how to improve the QOL while offering an alternative perspective on how to measure QOL. One could use the super-efficiency DEA models [31,32] to rank each individual city, however, the meaning of such ranking needs to be carefully examined. This is clearly a subject for future research and study.

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