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ABSTRACT

Effectiveness involves more than simple efficiency, which is limited to the production process assessment of peer operational units. Effectiveness incorporates both endogenous and exogenous variables. It is a fundamental driver for the success of an operational unit within a competitive environment in which either the liquidity of money in the market and the customers are considered to be scarce sources, or the New Public Management (NPM) is citizen/customer and goal-oriented. Additionally, with respect to short-run production constraints, the resources available and controllable by the operational units, as well as the legal status, we go beyond the traditional effectiveness assessment techniques by developing a modified or "rational" Quality-driven – Efficiency-adjusted DEA (MQE-DEA) model. This particular model provides a feasible effectiveness attainment path for every disqualified unit in order to meet high-perceived quality and high-efficiency standards. The input-output mix restructuring targets estimated by the original QE-DEA model are provided on a step-by-step basis in order to have realistic managerial implications.

Keywords: Effectiveness; Efficiency; Perceived Quality; Data Envelopment Analysis (DEA); context-dependent DEA

1. INTRODUCTION

Effectiveness goes beyond simple efficiency, which is concentrated on assessment of operational units' production process. Namely, in Service Units (SUs), effectiveness measurement incorporates efficiency and perceived quality, or customer/citizen satisfaction for the service received (Sherman & Zhu, 2006; Worthington & Dollery, 2000). Effectiveness attainment is deemed a mid – to – long term driver of success for every active unit, especially for those that operate in mature and highly competitive markets where customers are regarded as "scarce sources" (Hayes, 2008; Anderson & Fornell, 1994).

The scope of the present paper is the development of a deterministic effectiveness assessment model. This model identifies benchmark units and target input and output levels for units that do not meet the high-perceived quality and high-efficiency criteria, at the same time taking into account, the feasibility of the outcomes for effectiveness attainment in the short-run. In order to estimate attainable optimization targets for each sample Decision Making Unit (DMU) we modify the Quality-driven – Efficiency-adjusted Data Envelopment Analysis (QE-DEA) model, put forth by Zervopoulos and Palaskas (2010). The original QE-DEA model is based on the Quality-adjusted DEA (Q-DEA) approach introduced by Sherman and Zhu (2006) and has particular applicability to effectiveness assessment settings in which a trade-off underlies the determinants of effectiveness.

In the first section of this study we review the literature on the component methods of the modified QE-DEA (MQE-DEA) (e.g., DEA and context-dependent DEA). In the following section, we analyze the mathematical underpinning of the QE-DEA as well as the algorithm of the MQE-DEA model. Evidence of the MQE-DEA technique application to Citizen Service Centers is provided in the fourth section. Conclusions are presented in the last section of the paper.

2. LITERATURE REVIEW

Studies related to the MQE-DEA approach methods follow, stressing the DEA and context-dependent DEA methods in order to provide insight to the developed step-by-step effectiveness assessment technique and its contribution to the effectiveness measurement field.

2.1 Data Envelopment Analysis (DEA)

DEA is the dominant non-parametric method in the comparative efficiency assessment literature put forth by Charnes, Cooper and Rhodes (1978). The three scholars developed a mathematical programming technique for identifying, after a comparative assessment of the sample units' input-output transformation process, the efficiency benchmark operational units, or Decision Making Units (DMUs), and determining either the minimum input-fixed output mix (input orientation), or vice versa (output orientation). Based on the peer assessment, a "production function" or generally a "production possibility surface" is formed without imposing it as it happens with the related to DEA stochastic methods (e.g., Stochastic Frontier Analysis).

DEA is a deterministic, extremal method that lacks statistical underpinning (Coelli et al., 2005). As a result, the outcomes of this method are vulnerable to dimensionality problems, raised by Cooper et al. (2004), and data misspecification (Perelman & Satín, 2009; Cooper et al., 2007). In this context, we prefer to use the term "estimation" rather than "determination" or "calculation" for the efficiency scores and target input and output values assigned to the sample DMUs after DEA application.

The sample operational units selected for DEA efficiency assessment are deemed homogenous as they engage and produce various amounts of common inputs and outputs respectively.

A basic DEA model is the BCC (Banker, Charnes & Cooper, 1984) which assumes that Variable Returns to Scale (VRS) dominate the input-output transformation process. The BCC model seeks to reveal the operational units and compose the piece-wise linear reference set, with the maximum efficiency values (efficiency score (e) = 1, where $0 \le e \le 1$) respecting the convexity condition.

Additionally, by applying DEA optimization for each sample DMU, the optimal weights are assigned to input and output values in order to estimate the target input or output levels that lead the non-efficient DMUs ($e < 1$) to the relative efficiency frontier.

The formulas developed to apply the BCC model are presented below:

$$
\begin{aligned}
& e^* = \min e \\
\text{subject to} \quad & \sum_{j=1}^{n} \lambda_j x_{ij} \le e x_{io} \quad i = 1,\dots,m \\
& \sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{ro} \quad r = 1,\dots,s \\
& \sum_{j=1}^{n} \lambda_j = 1 \\
& \lambda_j \ge 0 \qquad j = 1,\dots,n
\end{aligned}
$$

where DMU_o stands for one of the sample DMUs under assessment, x_{io} and y_{ro} represent the i th input and r th output of DMU_o respectively, and *lambdas* (λ_j) are the input and output non-negative weights.

2.2 Context-dependent DEA

The context-dependent DEA methodology developed by Seiford and Zhu (2003) is a "rational" benchmarking technique that provides feasible input and output targets for efficiency attainment, taking into account short-term restrictions such as resources' availability and controllability over the inputs engaged. This "reasonable" approach of the original DEA method partitions the sample units into multiple efficiency reference sets. In other words, the first level best-practice frontier is the global efficiency benchmark formed solely by the operational units with efficiency score equal to unity and zero slacks. Unlike the traditional DEA models that cluster sample DMUs into two groups: efficient and inefficient, the context-dependent DEA classifies the remaining units, the inefficient ones, into second-level, third-level, and other lower-level best practice frontiers. The lower-level frontiers are considered intermediate or local targets (Zhu, 2009).

By assuming n-number sample DMUs that engage m inputs to produce s outputs, then J^1 defines the sample DMUs and E^1 the set of globally efficient units. In the same way, the remaining, non-efficient DMUs, are classified into local efficiency reference sets that are defined by $J^{l+1} = J^l - E^l \ (i = 1,\dots,n)$. When $l = 1$, the context-dependent DEA model becomes the traditional BCC. When $l = 2$, the second-level efficiency frontier is revealed.

The partitioning algorithm produces efficiency strata has the following properties:

Step 1: Apply the BCC model to estimate the first-level efficiency benchmark units (E^1) out of the J^1 dataset.

Step 2: If $J^{l+1} = \varnothing$, then stop.

Otherwise, remove the E^1 DMUs from J^1 to obtain $J^{l+1} = J^l - E^l$ subset and Reapply the BCC model.

Step 3: Let $l = l + 1$ and return to Step 2 until $J^{l+1} = \varnothing$; that is the stopping rule.

The multilayered efficiency frontier also serves as multi-evaluation context for the precedent and subsequent best-practice sets. Based on the intra-assessment process, between the efficiency frontiers, even of "equal performance" DMUs are ranked. The differentiation property of the context-dependent DEA is the outcome of the attractiveness and progress measures. The higher the attractiveness score, the better input-output transformation process a DMU applies (Zhu, 2003). On the contrary, the larger the progress value assigned to the operational unit, the less attractive it is, so greater restructuring is needed to reach the global efficiency frontier (ibid.).

3. QUALITY-DRIVEN – EFFICIENCY-ADJUSTED DEA (QE-DEA)

The QE-DEA model put forth by Zervopoulos and Palaskas (2010) relaxes the two-dimensional analysis of effectiveness. The two dimensions of effectiveness: perceived quality (q) and efficiency (e) are depicted on the x-axis and the y-axis respectively of the plane, while the perceived quality-efficiency bundle determines the geometrical position of a Service Unit (SU). The developed model adopts the classification methodology of the Q-DEA model (Sherman & Zhu, 2006) separating the chart into four segments: 1) high-perceived quality – high-efficiency (HQ-HE); 2) low-perceived quality – high-efficiency (LQ-HE); 3) low-perceived quality – low-efficiency (LQ-LE); and 4) high-perceived quality – low-efficiency (HQ-LE) (Figure 1). Additionally, efficiency and perceived quality cut-off levels are introduced to the chart limiting the feasible area of the two determinants of effectiveness to the interval (0.2, 1].

The feasible area determination, regarding the efficiency scores, derives from the work of Paradi et al. (2004), who revealed that faulty input and output data entries as well as missing values account for efficiency scores equal to or less than 0.2. Consequently, in case of efficiency scores as low as 0.2 or lower, the data entries should be reconsidered and cross-validated rather than embracing the efficiency results.

The original perceived quality scores are collected from questionnaire-based fieldwork research and classified into a five-point Likert scale response format (Table 1). To be more precise, the five-point response format allows the respondents to rate the satisfaction received by the service provided from the particular operational unit in an easily quantifiable way. For example, the five-point scale could stand for: 1 - very dissatisfied, 2 - dissatisfied, 3 - neither satisfied nor dissatisfied, 4 – satisfied, and 5 - very satisfied. Applying this format, the average perceived quality or satisfaction scores referred to each sample unit are expressed by the consecutive closed interval [1, 5].

The feasible area of the perceived quality or satisfaction scores is the conversion output of the five-point Likert scale into percentages. The conversion process relaxes the multiplication of the left-hand column scores in Table 1 by the value 0.2 leading to the right-hand column intervals of the same Table.

Table 1. Perceived Quality scores: five-point Likert scale conversion into percentages

Five-point Likert Scale	Perceived Quality Score Intervals Equivalent
1 to 1.99	[0.2, 0.4)
2 to 2.99	[0.4, 0.6)
3 to 3.99	[0.6, 0.8)
4 to 4.99	[0.8, 1)
5	[1]

With regard to Table 1, the feasible area of the perceived quality scores is determined by the adjusted interval [0.2, 1]. In this case, scores lower than 0.2 are excluded as a result of the full satisfaction rating conversion into percentage expressed by the unity and the adjusted quality score 0.2 respectively.

The algebraic analysis of the QE-DEA model that follows the geometric one introduces a constraint to prevent the starting formula of the developed model, Formula 1, to become null. Respecting this constraint ($q \neq 0.2$), the first left-hand end point adjusted perceived quality score interval in Table 1 becomes open (Table 2).

Additionally, considering a unitary high-perceived quality target area, the merger of the bottom two right column intervals in Table 1 is recommended. Under those circumstances, value 0.8 is regarded as a baseline of satisfaction, alternatively, of high-perceived quality. In the same way, operational units that receive perceived quality score equal to 0.8 or greater meet the high-quality criterion and those that are below this threshold ($q < 0.8$) are considered as low quality units.

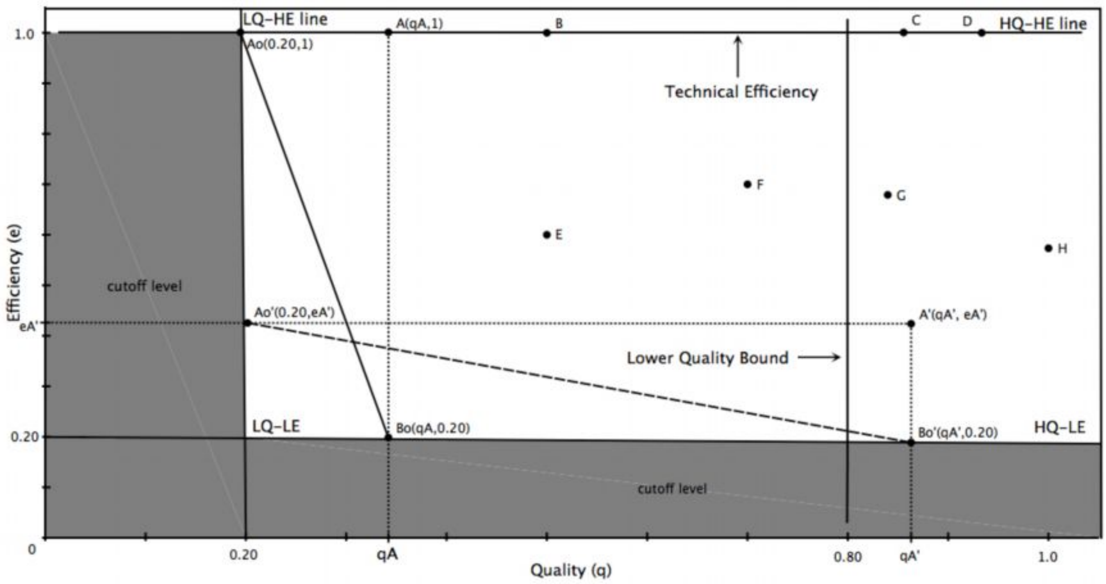
Table 2. Adjusted Perceived Quality Scores

Five-point Likert Scale	Adjusted Perceived Quality Score Intervals Equivalent
1 to 1.99	(0.2, 0.4)
2 to 2.99	[0.4, 0.6)
3 to 3.99	[0.6, 0.8)
4 to 5	[0.8, 1]

Regarding the aforementioned analysis, effective or high-perceived quality – high-efficiency (HQ-HE) units are considered those that simultaneously obtain a quality score equal to 0.8 or greater and an efficiency score equal to unity.

The novelty of the QE-DEA model is the zero-exclusion operational unit from the effectiveness assessment process. Unlike the Q-DEA model that suggests the removal of the low-quality – high-efficiency (LQ-HE) units from the evaluation sample in order to avoid any flaw in the determination of the benchmark/effective units, the QE-DEA model substituted the LQ-HE units by their hypothetical HQ-LE ones. The latter service units derive from the former after a boost to their perceived quality score sacrificing part of the efficiency standards (Figure 1). The actual and hypothetical units hold the same quality-efficiency mix.

Figure 1. Planar Analysis of Hypothetical SUs Development



It goes without saying that the assumption underlying the QE-DEA model is the inverse relationship between quality and efficiency. The trade-off between the two dimensions of effectiveness is met in many service sectors, such as bank branches, restaurant chain stores, one-stop-shops (De Bruijn, 2007; Sherman and Zhu, 2006; Athanassopoulos, 1997; Anderson and Fornell, 1994).

In the plane, we propose a downward movement of every LQ-HE operational unit to the HQ-LE segment respecting the original quality-efficiency relative size. Namely, in Figure 1, the LQ-HE SU 'A', specified by the coordinates of the point (q_A, 1) is directed to the point A' (q_A, e_A').

The QE-DEA model is based on a two-step algorithm:

Step 1: Run DEA (BCC) in order to estimate efficiency scores
Step 2: If the number of LQ-HE SUs is null, then stop.
Otherwise, before defining the hypothetical HQ-LE SUs out of the actual LQ-HE SUs, calculate the trade-off between quality and efficiency for each LQ-HE SU.
Next, determine the inputs of the hypothetical SUs keeping the outputs fixed (input oriented approach) and return to *Step 1*.

Adopting the QE-DEA algorithm, the best-practice frontier is formed solely by effective units that meet the high-perceived quality and high-efficiency standards. In other words, the benchmark SUs are exclusively those depicted in the HQ-HE line (Figure 1). The disqualified units appear in the HQ-LE and LQ-LE segments. After reapplying DEA, target input and output values result for the ineffective actual and hypothetical operational units[1] so as to meet the high-perceived quality and high-efficiency criteria.

Additionally, it should be highlighted that the efficiency score assigned to the hypothetical (LQ-HE) SUs is essential for the input variables' adjustment to high-perceived quality standards.

The input levels resulting from the second phase in Step 2 of the QE-DEA algorithm are estimated rather than determined because of the possible variation of the assigned weights. To be more precise, the second phase in Step 2 is detached from the DEA linear programming optimization formulae. As a result, the weights attached to the input variables of the hypothetical units (x_i') are expected to be an approximation of the final inputs, which will be calculated after returning to Step 1 and reapplying DEA. The same applies to the efficiency score of the hypothetical SUs (e.g. e_A'). What is computed by the first stage QE-DEA algorithm application (Step 1 and Step 2), may differ from the efficiency scores estimated reapplying DEA at the second stage analysis, after the completion of Step 2 of the QE-DEA algorithm. This possible deviation is due to the efficiency score sensitivity to data (input or output) perturbation. In this context, input variables' adjustment (e.g., increase) to high-perceived quality standards, when the outputs are fixed, does not necessarily lead to efficiency score decline.

Returning to Figure 1, subsequent to the determination of the two straight lines bounded by the points A_o, B_o and A_o', B_o' in the plane regarding the actual and the hypothetical operational units, respectively, the coordinates of quality (q_A') and efficiency (e_A') of the latter unit should be calculated. The quality score of the hypothetical unit is arbitrarily decided to be in the range of 0.8-1.0. The efficiency score (e_A') is determined after the computation of the distance function between equivalent point of the two straight lines. It should be pointed out that the symmetry between the two dimensions of effectiveness is fixed for the actual and hypothetical units A and A', respectively, so that the latter active unit is derived from the former.

$$\frac{(A_0 B_0)}{(A_0' B_0')} = \frac{(q_A - 0.20)(0.20 - 1)}{(q_A' - 0.20)(0.20 - e_A')} \qquad (1)$$

[1] In a planar coordinate system, hypothetical unit is regarded as a projection of an actual low-perceived quality – high-efficiency unit to high-perceived quality – low-efficiency segment holding the original perceived quality – efficiency symmetry.

Given the distance function formula: $(AB) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$ and substituting in (1) we take:

$$\frac{\sqrt{(q_A - 0.20)^2 + (0.20 - 1)^2}}{\sqrt{(q_A' - 0.20)^2 + (0.20 - e_A')^2}} = \frac{(q_A - 0.20)(0.20 - 1)}{(q_A' - 0.20)(0.20 - e_A')} \quad (2)$$

In general, even if diverse quality and efficiency cut-off points are chosen (cut-off points $\neq 0.2$), (2) is expressed by the following equation:

$$\frac{\sqrt{(q_A - q_0)^2 + (e_0 - 1)^2}}{\sqrt{(q_A' - q_0)^2 + (e_0 - e_A')^2}} = \frac{(q_A - q_0)(e_0 - 1)}{(q_A' - q_0)(e_0 - e_A')} \quad (3)$$

Equation (4) is the generalized formula [Appendix - Section 1] used to determine the efficiency scores (e_A') of the hypothetical SUs:

$$e_A' = e_0 + \sqrt{\frac{[(q_A - q_0)^2 (e_0 - 1)^2](q_A' - q_0)^2}{[(q_A - q_0)^2 + (e_0 - 1)^2](q_A' - q_0)^2 - (q_A - q_0)^2 (e_0 - 1)^2}} \quad (4)$$

Since the new efficiency score (e_A') has been calculated, the inputs of the hypothetical operational units should be adjusted holding the outputs fixed (input orientation).

Efficiency ratio was defined by Charnes et al. (1978):

$$e = \frac{\sum_{r=1}^{s} u_r y_r}{\sum_{i=1}^{m} v_i x_i} = \frac{u_1 y_1 + u_2 y_2 + ... + u_s y_s}{v_1 x_1 + v_2 x_2 + ... + v_m x_m} \quad (5)$$

where: e = efficiency score

y_r = amount of output r $\forall\ r = 1,...,s$

u_r = weight assigned to output r

x_i = amount of input i $\forall\ i = 1,...,m$

v_i = weight assigned to input i

Alternatively, the precedent equation (5) is expressed in matrix form:

$$e = \frac{\sum_{r=1}^{s} u_r y_r}{\sum_{i=1}^{m} v_i x_i} = \frac{[y_1, y_2, ..., y_s] \begin{bmatrix} u_1 \\ u_2 \\ ... \\ u_s \end{bmatrix}}{[x_1, x_2, ..., x_m] \begin{bmatrix} v_1 \\ v_2 \\ ... \\ v_m \end{bmatrix}} \quad (6)$$

Assuming technical efficiency prevails, then:

$$1 = \frac{[y_1, y_2, ..., y_s]\begin{bmatrix} u_1 \\ u_2 \\ ... \\ u_s \end{bmatrix}}{[x_1, x_2, ..., x_m]\begin{bmatrix} v_1 \\ v_2 \\ ... \\ v_m \end{bmatrix}}$$

Therefore, $$[x_1, x_2, ..., x_m]\begin{bmatrix} v_1 \\ v_2 \\ ... \\ v_m \end{bmatrix} = [y_1, y_2, ..., y_s]\begin{bmatrix} u_1 \\ u_2 \\ ... \\ u_s \end{bmatrix} \quad (7)$$

Functions (5)-(7) are applied for estimating the efficiency scores of actual SUs. In order to form hypothetical operational units, the inputs should be adjusted, given the input orientation of the analysis. In that case, functions (5)-(7) should be altered substantially:

$$e' = \frac{\sum_{r=1}^{s} u_r y_r}{\sum_{i=1}^{m} v_i x_i'}, \text{ where } e' \neq e \text{ and } x_i' \neq x_i \quad (8)$$

Expressing equation (8) in matrix form and conducting the required calculations [Appendix – Section 2], the input adjustment formula results:

$$\left.\begin{aligned} x_1' &= \frac{1}{e'} x_1 \\ x_2' &= \frac{1}{e'} x_2 \\ &... \\ x_m' &= \frac{1}{e'} x_m \end{aligned}\right\} \quad (9)$$

In the above system of equations, e' is known as far as it is the ordinate of the hypothetical point A′ (q_A', e_A'), namely, $e_k' = e_A'$. In general, e' is equal to the ordinate of every estimated HQ-LE hypothetical SU. Like the hypothetical efficiency score e', $x_i \ \forall \ i = 1,...,m$ is already known. To be more precise, x_i expresses the actual inputs of the LQ-HE SUs, or, the inputs of the SUs consist the original sample.

4. MODIFIED QE-DEA (MQE-DEA)

QE-DEA and context-dependent DEA form a realistic effectiveness assessment context for customer-oriented service organizations which is particularly applicable to cases in which inverse relationship connects the dimensions of effectiveness.

By taking into consideration the properties of the two methods, the QE-DEA algorithm is altered substantially:

Step 1: Run traditional DEA (BCC) in order to estimate efficiency scores.
Step 2: If the number of LQ-HE SUs is null, then apply the context-dependent DEA algorithm and stop.
Otherwise, before defining the hypothetical HQ-LE SUs of the actual LQ-HE SUs, calculate the trade-off between quality and efficiency for each LQ-HE SU.
Next, determine the inputs of the hypothetical SUs keeping the outputs fixed (input oriented approach)
Step 3: Introduce the hypothetical SUs, consequently the hypothetical inputs, to the dataset and apply the context-dependent DEA algorithm.

The modified QE-DEA model returns a deterministic step-by-step path for effectiveness attainment.

5. NUMERICAL EXAMPLE

5.1 Data description

The MQE-DEA model application is based on data from the Citizen Service Centers (CSCs), governmental one-stop service provision agencies. Fifty SUs comprise the sample, out of 1020 operating in Greece, serving about 60% of the citizens who visit CSCs for administrative issues. The number of inputs and outputs selected is six (number of full-time employees, weekly working hours, number of PCs, number of fax machines, number of printers, surface of each CSC) and three (number of electronic protocol registered services provided, number of manual services provided, number of served citizens) respectively.

The perceived quality or citizen satisfaction data collected through structured questionnaires is applied to each sample CSC separately. The fieldwork research was grounded on the SERVQUAL methodology put forth by Parasuraman et al. (1988). The dimensions of perceived quality selected were: responsiveness, assurance, reliability and physical facilities or tangibles. The number of questionnaires used to calculate the average perceived quality score for each sample CSC, after the exclusion of those deemed "unreliable" according to the Cronbach's Alpha criterion, is 1024.

5.2 MQE-DEA application

The first step of the MQE-DEA model requires sample SUs efficiency scores estimation and perceived quality determination. Adopting the MQE-DEA algorithm, the BCC model is applied for the SUs efficiency assessment.

Table 3. SUs Classification (1st stage)

Units	Efficiency Scores	Perceived Quality Scores	Classification	Units	Efficiency Scores	Perceived Quality Scores	Classification
1	1.0000	0.9230	HE-HQ	26	1.0000	0.8156	HE-HQ
2	0.9667	0.9304	LE-HQ	27	1.0000	0.8356	HE-HQ
3	1.0000	0.9431	HE-HQ	28	1.0000	0.8007	HE-HQ
4	0.9282	0.8208	LE-HQ	29	1.0000	0.9141	HE-HQ
5	0.6781	0.8600	LE-HQ	30	1.0000	0.9333	HE-HQ
6	0.8695	0.8736	LE-HQ	**31**	**1.0000**	**0.7793**	**HE-LQ**
7	0.8328	0.8185	LE-HQ	**32**	**1.0000**	**0.7763**	**HE-LQ**
8	0.7211	0.8704	LE-HQ	33	0.7462	0.7896	LE-LQ
9	0.7647	0.8733	LE-HQ	34	0.8226	0.9342	LE-HQ
10	1.0000	0.8111	HE-HQ	35	1.0000	0.9059	HE-HQ
11	0.8831	0.7815	LE-LQ	36	0.8014	0.8415	LE-HQ
12	0.9029	0.8637	LE-HQ	37	1.0000	0.8234	HE-HQ
13	0.6228	0.7926	LE-LQ	38	1.0000	0.8111	HE-HQ
14	1.0000	0.9689	HE-HQ	39	0.9976	0.8170	LE-HQ
15	1.0000	0.9496	HE-HQ	40	1.0000	0.9607	HE-HQ
16	0.6825	0.9430	LE-HQ	**41**	**1.0000**	**0.7904**	**HE-LQ**
17	1.0000	0.9037	HE-HQ	42	0.8844	0.7689	LE-LQ
18	0.6930	0.9274	LE-HQ	43	0.9084	0.8459	LE-HQ
19	1.0000	0.9467	HE-HQ	44	0.7994	0.8230	LE-HQ
20	1.0000	0.9452	HE-HQ	45	0.9089	0.8849	LE-HQ
21	1.0000	0.9689	HE-HQ	46	0.9211	0.9467	LE-HQ
22	0.9299	0.8081	LE-HQ	47	0.6659	0.9200	LE-HQ
23	1.0000	0.8076	HE-HQ	48	0.7172	0.9556	LE-HQ
24	1.0000	0.8103	HE-HQ	**49**	**1.0000**	**0.6659**	**HE-LQ**
25	1.0000	0.8719	HE-HQ	**50**	**1.0000**	**0.6941**	**HE-LQ**

The first stage MQE-DEA assessment results in 21 HE-HQ, 5 HE-LQ, 4 LE-LQ and 20 LE-HQ SUs. While HE-LQ SUs ≠ $\varnothing$, the MQE-DEA second stage analysis is activated in order to identify the hypothetical counterparts of the HE-LQ operational units. Namely, the 5 HE-LQ SUs are removed from the sample and replaced by an equal number of LE-HQ hypothetical units that keep the input-output symmetry of the actual units fixed.

By applying Formula (4) of the QE-DEA model and arbitrarily selecting the minimum high-perceived quality value ($q = 0.800$) we estimate the efficiency scores of the hypothetical units. Respecting the assumption of the QE-DEA model that a trade-off between efficiency and perceived quality appears, the increase of the perceived quality levels leads to efficiency score decline.

Table 4. HE-LQ Units' Efficiency Scores Adjustment through QE-DEA Model Application (2nd stage)

Actual Units				Hypothetical Units			
Units	Efficiency Scores (e)	Perceived Quality Scores (q)	Classification	Units	Efficiency Scores (e')	Perceived Quality Scores (q')	Classification
31	1.0000	0.7793	HE-LQ	31'	0.9527	0.8000	LE-HQ
32	1.0000	0.7763	HE-LQ	32'	0.9462	0.8000	LE-HQ
41	1.0000	0.7904	HE-LQ	41'	0.9776	0.8000	LE-HQ
49	1.0000	0.6659	HE-LQ	49'	0.7430	0.8000	LE-HQ
50	1.0000	0.6941	HE-LQ	50'	0.7891	0.8000	LE-HQ

The perceived quality rise requires additional resources engagement. As a result, the hypothetical SUs use higher level of inputs than their actual counterparts. The hypothetical input levels are calculated by the Formula (9) application of the QE-DEA model.

Table 5. Hypothetical Input Data (2nd stage)

Units	Status	Full-time Employees	Working Hours	PC	Fax	Printers	Surface
31	A	5	33	4	0	2	50
31	H	5	35	4	0	2	52
32	A	18	63	14	2	4	80
32	H	19	66.5	15	2	4	85
41	A	5	37.5	9	1	3	80
41	H	5	38	9	1	3	82
49	A	3	36.5	2	0	1	150
49	H	4	49	3	0	1	202
50	A	4	32.5	2	1	2	180
50	H	5	41	3	1	3	228

[A]: Actual, [H]: Hypothetical

The second stage of the MQE-DEA algorithm application ensures the lack of HE-LQ SUs in the dataset.

By running the following stage of the same algorithm and introducing the quality adjusted input values to the hypothetical SUs, firstly the new efficiency scores of the sample units are estimated (Appendix: Table 6A), and secondly the global and local best-practice frontiers are revealed. Regardless the increase on input levels of the quality adjusted SUs, their relative efficiency scores are not alienated from unity. Acknowledging the sensitivity of the efficiency scores resulted from the MQE-DEA algorithm, which produces non-comparative – DEA-detached results, we adopted the term "estimation" rather than "determination" since the beginning of this paper.

The top-ranked reference set, Level 1, includes eleven SUs, two of which (SU31 and SU32) are hypothetical (Table 6). Level 1 is regarded as the optimum effectiveness benchmark for the SUs from the lower-level frontier while all the operational units are simultaneously HE-HQ and slack-free. The location of the remaining three quality-adjusted SUs on lower level best-practice frontiers is due to the non-zero slacks of their production process. In fact, SUs 31 and 32 are benchmarks for many of their sample counterparts, unlike SU51 which is not a target for any peer (Appendix: Table 6B).

Table 6**.** SUs and Efficiency-Perceived Quality Classification (3rd stage)

Levels					
1	2	3	4	5	6
1 (HE-HQ)	2 (LE-HQ)	4 (LE-HQ)	11 (LE-LQ)	10 (HE-HQ)	**50 (HE-HQ)**
20 (HE-HQ)	3 (HE-HQ)	8 (LE-HQ)	15 (HE-HQ)	16 (LE-HQ)	
23 (HE-HQ)	5 (LE-HQ)	9 (LE-HQ)	22 (LE-HQ)	34 (LE-HQ)	
26 (HE-HQ)	6 (LE-HQ)	12 (LE-HQ)	33 (LE-LQ)	35 (HE-HQ)	
27 (HE-HQ)	7 (LE-HQ)	13 (LE-LQ)	42 (LE-LQ)	39 (LE-HQ)	
28 (HE-HQ)	14 (HE-HQ)	18 (LE-HQ)	45 (LE-HQ)	44 (LE-HQ)	
30 (HE-HQ)	17 (HE-HQ)	21 (HE-HQ)			
31 (HE-HQ)	19 (HE-HQ)	29 (HE-HQ)			
32 (HE-HQ)	24 (HE-HQ)	43 (LE-HQ)			
38 (HE-HQ)	25 (HE-HQ)	46 (LE-HQ)			
40 (HE-HQ)	36 (LE-HQ)	47 (LE-HQ)			
	37 (HE-HQ)	48 (LE-HQ)			
	41 (HE-HQ)	**49 (HE-HQ)**			

We already have pointed out that the MQE-DEA method is a realistic approach for effectiveness assessment. For instance, comparing the one-step and two-step scenarios for effectiveness improvement of a Level 3 SU (e.g., SU12), it is obvious that the intermediation of a best practice frontier results in less radical interventions to the production process. Namely, the two-step approach returns smoother modifications to the input levels than the one-step strategy.

Table 7. Feasible Targets Identification (Progress Potentials)

Steps	Current Status (SU/Level)	Evaluation Context (Level)	Target Inputs /(% Change) FT-Employees	Working Hours	PC	Fax	Printers	Surface
1	SU 12/Level 3	Level 1	3 (-50.0%)	15.5 (-51.9%)	3 (-57.1%)	0 (-100.0%)	1 (-66.7%)	28 (-70.5%)
1	SU 12/Level 3	Level 2	4(-33.3%)	21 (-34.9%)	4 (-42.9%)	1 (0.0%)	2 (-33.3%)	33 (-65.3%)
2	SU 12/Level 2	Level 1	3 (-25.0%)	16 (-23.8%)	3 (-25.0%)	0 (-100.0%)	1 (-50.0%)	25 (-24.2%)

6. CONCLUSION REMARKS AND FURTHER RESEARCH

SUs' operational success is not only a matter of production process optimization detached from exogenous variables. In this context, stand-alone efficiency measurement, which is concentrated on input-output transformation process assessment, cannot ensure mid – to - long term success or even viability for a unit that acts in a competitive environment.

In this paper, we develop an effectiveness assessment method that yields endogenous and exogenous variable sensitive target input values (input-oriented approach). The introduced method discharges the mainstream microeconomic theory of all-time profit maximization, indicating the optimum production at the output maximization – input minimization level. It proposes additional resources' engagement (investment) in order to achieve customer satisfaction and loyalty, secure the current sales level, and even look for a higher level. Such a strategy is deemed extroverted in comparison with the introverted efficiency-oriented approaches.

The developed MQE-DEA model estimates feasible short and long term optimization solutions for SUs production process. By sacrificing the profit maximization concept, it identifies "balanced" input and output levels that meet the optimum endogenous and exogenous variables mix. The MQE-DEA model has substantial applicability when a trade-off underlies the controllable and non-controllable determinants of effectiveness.

Further research is needed to develop an output-oriented MQE-DEA model and to extend the current one when non-discretionary input and output variables appear. Additionally, the two-dimensional MQE-DEA technique could be applied to multi-dimensional settings when multiple contextual variables determine effectiveness.

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APPENDIX

Section 1

Equation (3) can be rewritten as:

$$\frac{(q_A - q_0)^2 + (e_0 - 1)^2}{(q_A' - q_0)^2 + (e_0 - e_A')^2} = \frac{(q_A - q_0)^2 (e_0 - 1)^2}{(q_A' - q_0)^2 (e_0 - e_A')^2}$$

$$[(q_A - q_0)^2 + (e_0 - 1)^2](q_A' - q_0)^2 (e_0 - e_A')^2 = [(q_A' - q_0)^2 + (e_0 - e_A')^2](q_A - q_0)^2 (e_0 - 1)^2$$

Let $$c_1 = [(q_A - q_0)^2 + (e_0 - 1)^2]$$

and $$c_2 = (q_A - q_0)^2 (e_0 - 1)^2$$

Then $$c_1 (q_A' - q_0)^2 (e_0 - e_A')^2 = [(q_A' - q_0)^2 + (e_0 - e_A')^2] c_2$$

$$c_1 (q_A' - q_0)^2 (e_0 - e_A')^2 = c_2 (q_A' - q_0)^2 + c_2 (e_0 - e_A')^2$$

$$c_1 (q_A' - q_0)^2 (e_0 - e_A')^2 - c_2 (e_0 - e_A')^2 = c_2 (q_A' - q_0)^2$$

$$(e_0 - e_A')^2[c_1(q_A' - q_0)^2 - c_2] = c_2(q_A' - q_0)^2$$

$$(e_0 - e_A')^2 = \frac{c_2(q_A' - q_0)^2}{c_1(q_A' - q_0)^2 - c_2}$$

$$|e_0 - e_A'| = \sqrt{\frac{c_2(q_A' - q_0)^2}{c_1(q_A' - q_0)^2 - c_2}}$$

$$e_0 - e_A' = +\sqrt{\frac{c_2(q_A' - q_0)^2}{c_1(q_A' - q_0)^2 - c_2}} \quad \text{or} \quad e_0 - e_A' = -\sqrt{\frac{c_2(q_A' - q_0)^2}{c_1(q_A' - q_0)^2 - c_2}}$$

The first critical value:

$$e_0 - e_A' = +\sqrt{\frac{c_2(q_A' - q_0)^2}{c_1(q_A' - q_0)^2 - c_2}}$$

$$e_A' = e_0 - \sqrt{\frac{c_2(q_A' - q_0)^2}{c_1(q_A' - q_0)^2 - c_2}}$$

is rejected because the condition: $e_A' > e_0$ is not satisfied.

On the contrary, the alternative critical value:

$$e_0 - e_A' = -\sqrt{\frac{c_2(q_A' - q_0)^2}{c_1(q_A' - q_0)^2 - c_2}}$$

$$e_A' = e_0 + \sqrt{\frac{c_2(q_A' - q_0)^2}{c_1(q_A' - q_0)^2 - c_2}}$$

is accepted, because the condition: $e_A' > e_0$ is satisfied.

The generalized formula is the following:

$$e_A' = e_0 + \sqrt{\frac{[(q_A - q_0)^2(e_0 - 1)^2](q_A' - q_0)^2}{[(q_A - q_0)^2 + (e_0 - 1)^2](q_A' - q_0)^2 - (q_A - q_0)^2(e_0 - 1)^2}} \qquad (4)$$

Section 2

Equation (8) can be expressed in matrix form:

$$e' = \frac{[y_1, y_2, \ldots, y_s]\begin{bmatrix} u_1 \\ u_2 \\ \ldots \\ u_s \end{bmatrix}}{[x_1', x_2', \ldots, x_m']\begin{bmatrix} v_1 \\ v_2 \\ \ldots \\ v_m \end{bmatrix}}$$ (multiplying both sides by $\frac{1}{e'}$, where $e' \neq 0$)

$$\frac{e'}{e'}=\frac{[y_1,y_2,...,y_s]\begin{bmatrix}u_1\\u_2\\...\\u_s\end{bmatrix}}{e'[x_1',x_2',...,x_m']\begin{bmatrix}v_1\\v_2\\...\\v_m\end{bmatrix}}$$

$$1=\frac{[y_1,y_2,...,y_s]\begin{bmatrix}u_1\\u_2\\...\\u_s\end{bmatrix}}{[e'x_1',e'x_2',...,e'x_m']\begin{bmatrix}v_1\\v_2\\...\\v_m\end{bmatrix}} \tag{8a}$$

Introducing (8a) to equation (7):

$$1=\frac{[x_1,x_2,...,x_m]\begin{bmatrix}v_1\\v_2\\...\\v_m\end{bmatrix}}{[e'x_1',e'x_2',...,e'x_m']\begin{bmatrix}v_1\\v_2\\...\\v_m\end{bmatrix}}$$

$$[e'x_1',e'x_2',...,e'x_m']\begin{bmatrix}v_1\\v_2\\...\\v_m\end{bmatrix}=[x_1,x_2,...,x_m]\begin{bmatrix}v_1\\v_2\\...\\v_m\end{bmatrix} \tag{8b}$$

Equation (8b) leads to the input adjustment formula:

$$\left.\begin{matrix}x_1=e'x_1'\\x_2=e'x_2'\\...\\x_m=e'x_m'\end{matrix}\right\} \quad \text{or} \quad \left.\begin{matrix}x_1'=\dfrac{1}{e'}x_1\\x_2'=\dfrac{1}{e'}x_2\\...\\x_m'=\dfrac{1}{e'}x_m\end{matrix}\right\}$$

Section 3

$$\sum_{i=1}^{m} x_i' = \frac{1}{e'}\sum_{i=1}^{m} x_i \qquad (10a)$$

Tables

Table 6A. BCC DEA Application for Efficiency Scores Estimation and SUs Classification

SUs	Efficiency Score	Classification	SUs	Efficiency Score	Classification
1	1.0000	HE - HQ	26	1.0000	HE - HQ
2	0.9882	LE - HQ	27	1.0000	HE - HQ
3	1.0000	HE - HQ	28	1.0000	HE - HQ
4	0.9291	LE - HQ	29	1.0000	HE - HQ
5	0.7067	LE - HQ	30	1.0000	HE - HQ
6	0.8850	LE - HQ	**31**	**1.0000**	**HE - HQ**
7	0.8559	LE - HQ	**32**	**1.0000**	**HE - HQ**
8	0.7218	LE - HQ	33	0.7461	LE - LQ
9	0.7655	LE - HQ	34	0.8240	LE - HQ
10	1.0000	HE - HQ	35	1.0000	HE - HQ
11	0.8839	LE - LQ	36	0.8088	LE - HQ
12	0.9129	LE - HQ	37	1.0000	HE - HQ
13	0.6324	LE - LQ	38	1.0000	HE - HQ
14	1.0000	HE - HQ	39	0.9976	LE - HQ
15	1.0000	HE - HQ	40	1.0000	HE - HQ
16	0.6839	LE - HQ	**41**	**1.0000**	**HE - HQ**
17	1.0000	HE - HQ	42	0.9053	LE - LQ
18	0.7063	LE - HQ	43	0.9087	LE - HQ
19	1.0000	HE - HQ	44	0.7993	LE - HQ
20	1.0000	HE - HQ	45	0.9094	LE - HQ
21	1.0000	HE - HQ	46	0.9371	LE - HQ
22	0.9298	LE - HQ	47	0.6759	LE - HQ
23	1.0000	HE - HQ	48	0.7184	LE - HQ
24	1.0000	HE - HQ	**49**	**1.0000**	**HE - HQ**
25	1.0000	HE - HQ	**50**	**1.0000**	**HE - HQ**

Table 6B. Hypothetical Units Benchmarking

Hypothetical Target Units	Units
31	2, 5, 8, 11, 12, 16, 18, 1 34, 43, 44, 45, 46, 47, 48
32	2, 5, 6, 7, 8, 9, 13, 18, 1 36, 47
41	4
49	42
50	