

A RATIONAL ROAD TO EFFECTIVENESS ATTAINMENT

Panagiotis Zervopoulos

Department of Economic and
Regional Development,
Panteion University of Athens,
136 Syngrou Avenue, Athens,
Greece

panagiotis.zervopoulos@gmail.com

Francisco Vargas*

Economics Department,
Universidad de Sonora
E. de Zubeldía No. 27
Hermosillo, Sonora,
Mexico

fvargas@guaymas.uson.mx

Gang Cheng

China Center for Health
Development Studies,
Peking University,
38 Xueyuan Rd, Haidian
District, Beijing, China

chenggang@bjmu.edu.cn

ABSTRACT

Operational effectiveness goes beyond efficiency while it incorporates exogenous variables, non-controllable by the service units. Effectiveness is a fundamental driver for the success of an operational unit within a competitive environment. In this context, we seek to identify the active units that meet both the high or technical efficiency and the perceived high quality criteria. We also aim to develop a roadmap for effectiveness for every operational unit and we consider the feasibility of the results produced by the effectiveness assessment process in the short run. The target values uncovered by comparative optimization techniques (e.g. Data Envelopment Analysis) for efficiency and effectiveness measurement generally have limited managerial implications due to production constraints, available resources, and legal status. This paper introduces a modified Quality-driven – Efficiency-adjusted Data Envelopment Analysis (MQE-DEA) model to assess effectiveness and provide a step-by-step path to achieve high quality and high efficiency in every operational unit under evaluation. The MQE-DEA model has particular applicability to the effectiveness assessment of homogenous service units in which an inverse relationship underlies the two dimensions of effectiveness embraced in this study (e.g. bank branches, restaurant chain stores, governmental one-stop-shops).

Keywords: Data Envelopment Analysis (DEA); context-dependent DEA; effectiveness; efficiency; perceived quality.

1. INTRODUCTION

Efficiency-related optimization techniques (e.g. Data Envelopment Analysis, Stochastic Frontier Analysis) cannot ensure operational units' prosperity or even viability in a mature market in which market shares' variability is marginal, opportunities for profitability growth are limited and competition is intense. In such markets, operational units' strategy should incorporate, besides efficiency optimization, customer satisfaction or perceived quality. Thus, the use of the term effectiveness seems more appropriate than efficiency to describe a holistic approach to modern, customer-oriented, organizational strategic planning. On the contrary, remaining solely loyal to introversion, such as input-output transformation process optimization, without considering exogenous variables and while operating in mature markets leads to a loop

that ends with the shrinkage of a unit or even its silence.

The scope of the present study is the development of an effectiveness assessment model that elaborates efficiency and perceived quality data for every sample operational unit. The new model relies on the Quality-driven – Efficiency-adjusted DEA (QE-DEA) method put forth by Zervopoulos and Palaskas (2011). In advance, it introduces a time-variance assumption in order to determine feasible short-term targets for the sample units that fail to meet high standards of efficiency and perceived quality. In this paper, efficiency and perceived quality are deemed the dimensions of effectiveness.

The QE-DEA model is applicable to assess comparative effectiveness in case an inverse relationship appears between the dimensions of effectiveness. It suggests a customer-oriented strategy for every operational unit, letting the

customers be the drivers of the organizational operations. In this context, the need for organizational restructuring is quality-driven towards optimized efficiency and improved customer satisfaction. According to the QE-DEA model, qualified operational units are solely those that meet both high quality perception and high efficiency criteria.

In this paper, a modified Quality-driven – Efficiency-adjusted DEA (MQE-DEA) model is introduced, putting emphasis on output-orientation. The new model is time-sensitive, respecting the implications of time in restructuring the production process to achieve the greatest effectiveness. To be more precise, the targets yielded by applying the MQE-DEA model are feasible in the short run. Moreover, the benchmarks identified are “strong”. They not only are effective, but their production process is free of slacks, and they are the most referenced units by their disqualified counterparts to achieve effectiveness.

The second section of this study discusses the literature review on methodologies on which the MQE-DEA model is grounded. In the following section, the QE-DEA model is presented and in the fourth section, the mathematical underpinning of the MQE-DEA model is analyzed. In the fifth section, the MQE-DEA model is applied to data from governmental one-stop-shop agencies, called Citizen Service Centers (CSCs). Concluding remarks are presented in the last section of the paper.

2. LITERATURE REVIEW

The studies related to the MQE-DEA model’s development methods are discussed below in order to present the properties and weaknesses of the current techniques. The intent of this discussion is to provide an understanding of the effectiveness assessment field and the mathematical underpinnings.

2.1 DATA ENVELOPMENT ANALYSIS (DEA)

DEA is a deterministic comparative efficiency assessment method for homogeneous¹ operational units’ benchmarking. The best practice units identified by DEA are regarded as reference units for the remaining sample under evaluation. Consequently, DEA serves

¹ Homogeneous are those that engage common resources to produce common goods or services operating diverse production processes.

not only as a benchmarking technique but also as a tool to determine quantitative target input or output values to attain optimum efficiency.

This particular method, relying on linear programming, makes no assumption on the underlying production function of each sample operational unit. Unlike its rival efficiency evaluation methods (e.g. Stochastic Frontier Analysis), DEA empirically estimates an optimum production function, or the best-practice frontier, formed by the reference units’ input-output data.

DEA elaborates input and output data to calculate efficiency, at the same time taking into account the impact of returns to scale on the efficiency status of every sample operational unit. To be more precise, there are two main approaches in DEA literature regarding incorporation of the returns to scale. The seminal paper put forth by Charnes, Cooper and Rhodes (1978) assumes that constant returns to scale prevail upon all the sample operational units’ production process. As a result, active units may be deemed inefficient merely because of their disagreement with the arbitrarily selected returns to scale. The second approach, developed by Banker, Charnes and Cooper (1984), called the BCC model, is more adaptive than the previous one while respecting the variation in returns to scale between the operational units production process. In this case, the efficiency results yielded and the best-practice frontier formed by the BCC-DEA model are more representative of the reality.

Another major breakdown of the DEA method is that the orientation of the analysis better fits the disposability of modifications on either input or output variables. It is common that restrictions applied to the units under assessment, such as availability of resources or protectionism (e.g. in public organizations) on one hand, and market maturity and intense competition on the other hand, become the drivers of the orientation selection by the operational units’ policymakers. The input or output-oriented DEA aims to calculate the minimum input values (target inputs), holding the outputs fixed, or to determine the maximum output levels (target outputs), keeping the original inputs unaltered. For instance, in case DEA is applied to public organizations in which protectionism appears over the input variables, especially the number of employees occupied, an output-oriented analysis is more appropriate.

Translating the DEA comparative efficiency assessment concept into linear programming

formulae respecting the returns to scale variance as well as the output orientation (BCC-DEA output), results:

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

where γ^* is the efficiency score of the o th operational unit, the subscript “o” denotes the sample operational unit currently assessed, x_{io} and y_{ro} stand for the i th input and the r th output of the o th unit respectively, and the lambdas (λ_j) represent the input and output non-negative weights.

2.2 CONTEXT-DEPENDENT DEA

The Context-dependent DEA method put forth by Seiford and Zhu (2003) is regarded as a rational adjustment on DEA outcomes. In other words, considering the feasibility of the target inputs or outputs suggested by DEA for the sample’s inefficient units due to short-term restrictions, the Context-dependent DEA method introduces milestones towards attaining efficiency. Assuming that the best-practice frontier formed by the traditional DEA is a “global” reference set adopted by Context-dependent DEA as well, intermediate frontiers, or “local” reference sets, are specified by the latter method in order to define feasible short-term targets for the units that lack efficiency. As a result, the sample operational units are classified into multilayered efficiency frontiers.

In order to implement the sample partitioning concept, Seiford and Zhu (2003) consider an n -number operational units’ sample with a dataset consisting of m inputs and s outputs. By assuming that \mathcal{Q}^l denotes the n -units and R^l the set of efficient and zero-slack units located on the “global” reference set, the remaining active units, the “weak” efficient or the inefficient units, are clustered around the $\mathcal{Q}^{l+1} = \mathcal{Q}^l - R^l \quad \forall l=1, \dots, n$ sets ($R^l \cap R^{l+1} = \emptyset$ and $R^l \cup R^{l+1} = \mathcal{Q}^l$).

Respecting the variable returns to scale orientation of the study, the clustering algorithm is written:

Step 1: Run the BCC-DEA model to identify the units that compose the “global”

reference set (R^l)

Step 2: a. If $\mathcal{Q}^{l+1} = \emptyset$, then stop.

b. Otherwise, eject the R^l units from the \mathcal{Q}^l set to obtain the $\mathcal{Q}^{l+1} = \mathcal{Q}^l - R^l$ subset and rerun the BCC-DEA model.

Step 3: Let $l=l+1$ and go back to *Step 2* until

$\mathcal{Q}^{l+1} = \emptyset$.

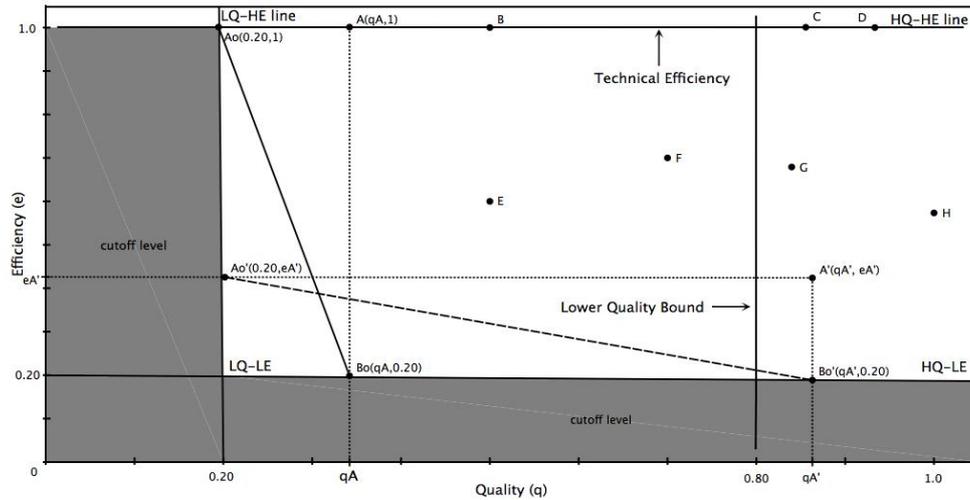
$\mathcal{Q}^{l+1} = \emptyset$ is the stopping rule.

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

The QE-DEA method developed by Zervopoulos and Palaskas (2011) is deemed a reverse approach to the mainstream effectiveness-based DEA measurements while it sets customer satisfaction as the core element in the operational units’ strategic planning process. QE-DEA overcomes a weakness of the Quality-adjusted DEA (Q-DEA) model (Sherman and Zhu, 2006), and also tackles problems of the DEA method. To be more precise, Q-DEA suggests the removal from the comparative effectiveness assessment process of the units that merely meet the efficiency criterion. By interpreting the impact of this decision in a strategic setting, the removed unit is condemned to competitiveness “emasculatation” while it is not allowed to identify its comparative weaknesses. Additionally, traditional DEA fails to specify best practice units that simultaneously meet high-efficiency and high-perceived quality standards when a trade-off underlies the dimensions of effectiveness. As a result, quality is handled mostly as an output variable, assuming that monotonicity prevails between inputs and outputs (Soteriou & Zenios, 1999; Chilingerian & Sherman, 1990; Bessent et al., 1984).

QE-DEA relies on the planar analysis of the QE-DEA model locating the sample operational units into four quadrants: a) high-perceived quality – high-efficiency (HQ-HE); b) low-perceived quality – high-efficiency (LQ-HE); c) low-perceived quality – low-efficiency (LQ-LE); and d) high-perceived quality – low-efficiency (HQ-LE) (Figure 1). Additionally, an active area for efficiency and perceived quality is the interval (0.2, 1]. The active area decision is based on the scaling into percentage of the five-point Likert scale format, applied for the customer satisfaction survey conducted in order to specify each sample unit’s quality score, and on the work of Paradi et al. (2004) regarding the accuracy of the DEA results.

Figure 1. QE-DEA Concept Planar Analysis



Unlike the Q-DEA model, QE-DEA suggests replacement of the high-efficiency and low-quality units (i.e. unit A located on the LQ-HE segment) by the hypothetical counterparts (i.e. unit A' located on the HQ-LE segment) to emulate the original unit's perceived quality – efficiency symmetry. The latter model supports the underlying trade-off between the dimensions of effectiveness that appears in numerous markets such as restaurant chain stores and governmental one-stop-shops (De Bruijn, 2007; Sherman & Zhu, 2006).

In order to apply the properties of the output-oriented QE-DEA model the following algorithm has been developed:

- Step 1: Apply output-oriented BCC-DEA in order to identify sample operational units' efficiency scores
- Step 2: If LQ-HE units = \emptyset , then stop. Otherwise, prior to modification of the actual LQ-HE units into hypothetical HQ-LE, determine the trade-off between the dimensions of effectiveness for every LQ-HE unit. Next, calculate the outputs of the hypothetical units holding the inputs fixed and return to Step 1.

In case LQ-HE units = \emptyset , the output-oriented QE-DEA model coincides with the traditional output-oriented BCC-DEA model.

The aim of the QE-DEA model is the identification of the effective operational units, namely the units classified in the HQ-HE segment and the development of a roadmap for the disqualified units to attain effectiveness.

4. OUTPUT-ORIENTED MQE-DEA

The input-oriented modified Quality-driven – Efficiency-adjusted DEA (MQE-DEA) model put forth by Brissimis and Zervopoulos (2011) is altered substantially in order to comply with the output-oriented application of the QE-DEA model in conjunction with Context-dependent DEA. The combination of the two methods results in a feasible short-term effectiveness assessment framework for service organizations that seek to maximize the outputs produced and the customers' perceived quality of service holding the inputs used fixed. Like the original QE-DEA model, its modified version has enhanced applicability in case an inverse relationship underlies efficiency and perceived quality.

The time-awareness of the MQE-DEA model for identifying best-practice solutions for the operational units under assessment strengthens its managerial implication. In other words, the target outputs calculated for the ineffective or “weak” effective units respect the difficulties in increasing the market share of these particular units, increasing their customer base and their revenues in the short-run.

A major classification is applied by the MQE-DEA model to the sample units to distinguish the “strong” from the “weak” effective units and the ineffective ones. “Strong” effective operational units are those comprising the “global” effectiveness frontier. “Weak” effective units are those that merely meet the high-perceived quality and high-efficiency standards while slacks appear in their production process. As a result, they have limited impact on either the remaining “weak” effective units or the ineffective ones. The

more the operational units under assessment comply with the MQE-DEA standards, the higher level their reference set.

The properties of the output-oriented MQE-DEA model rely on a three-stage algorithm:

Step 1: Apply the output-oriented BCC-DEA model for specifying sample operational units efficiency scores.

Step 2: If LQ-HE sample units = \emptyset , then run the output-oriented Context-dependent DEA algorithm and stop.

Otherwise, determine the trade-off between the dimensions of effectiveness and define the hypothetical operational units.

Next, specify the outputs of the hypothetical units holding the inputs fixed.

Step 3: Replace the actual units with their hypothetical counterparts and run the output-oriented Context-dependent DEA algorithm.

The planar analysis of the output-oriented MQE-DEA model is similar to that of the QE-DEA model presented in Figure 1 in section 3. The quality score for every sample unit is the average customer satisfaction rating reported. In order to collect the ratings fieldwork research is conducted. A five-point Likert scale response format has been used for the customer satisfaction data collection, and is easily transformed into percentages in order to be symmetrical to the scale used for the efficiency scores.

To apply the properties of the output-oriented MQE-DEA algorithm, we initially develop a formula that secures the perceived quality-efficiency symmetry of the actual LQ-HE units to the hypothetical ones:

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

The distance function formula

$(AB) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$ introduced in formula (1) results:

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

A generalized formula is presented below in which the researcher or the policymaker may decide the cut-off points and consequently the active area of the efficiency and perceived quality.

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

By conducting the appropriate calculations [Appendix – Section 1], a generalized formula for hypothetical efficiency scores (e_A') determination is revealed:

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

The second phase of the MQE-DEA algebraic analysis to calculate the hypothetical outputs is based on the efficiency ratio (Charnes et al., 1978):

$$e = \frac{\sum_{r=1}^s u_r y_r}{\sum_{i=1}^m v_i x_i} \quad (5)$$

where: e = efficiency score

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

u_r = weight assigned to output r

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

v_i = weight assigned to input i

Let the efficiency score be equal to unity

$$1 = \frac{\sum_{r=1}^s u_r y_r}{\sum_{i=1}^m v_i x_i} \quad (6)$$

or,
$$\sum_{i=1}^m v_i x_i = \sum_{r=1}^s u_r y_r \quad (7)$$

Towards the determination of the hypothetical outputs, while the inputs are fixed and the hypothetical efficiency score is known from formula (4), we alter substantially formula (5).

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

Following the calculations presented in Section 2 of the Appendices, the output values of the hypothetical units are specified.

$$\left. \begin{aligned} y_1' &= e' y_1 \\ y_2' &= e' y_2 \\ \dots \\ y_s' &= e' y_s \end{aligned} \right\} \quad (9)$$

5. Numerical Example

5.1 Data Description

The data used for the MQE-DEA application came from the Citizen Service Centers (CSCs), which are decentralized one-stop-shops that provide administrative services. The sample consists of 50 units out of 1020 that operate in Greece. Although the sample selected represents 4.9% of the population, the sample units serve around 60% of the citizens who utilize CSCs for administrative issues. Regarding the input and output variables, the former total six (number of full-time employees, weekly working hours, number of PCs, number of fax machines, number of printers and surface of each CSC), and the latter total three (number of electronic protocol registered services, number of manual services and number of citizens received administrative services by the CSCs).

For the perceived quality or customer satisfaction data, structured questionnaires were administered to citizens who already received a service by the reference CSC. The citizens who participated in the fieldwork research should have had previous personal

experience regarding the quality of services provided by the same CSC. About 20 answers per CSC finally were used to determine the perceived quality score of the sample units. To be more precise, 1024 fully answered questionnaires were introduced to the MQE-DEA model after the rejection of the “unreliable” questionnaires, according to the Cronbach’s Alpha criterion results. Based on the SERVQUAL method developed by Parasuraman et al. (1988), the questionnaire developed consisted of four determinants of perceived quality: 1) responsiveness; 2) assurance; 3) reliability and 4) physical facilities of tangibles.

5.2 Output-oriented MQE-DEA application

The aim of the output-oriented MQE-DEA model is to identify the “global” benchmarks, or the sample units that simultaneously meet the high-perceived quality and the high-efficiency standards, and also a production process free of slacks. For the remaining units, which are located in the “local” best-practice frontier, target output levels specified are greater than the original output data, holding the input levels fixed and respecting the need to attain high-perceived quality. It is expected the target output yielded by the MQE-DEA application to be less than that resulted from the DEA application towards efficiency optimization.

By applying the first step of the output-oriented MQE-DEA algorithm, the efficiency and the perceived quality scores of the sample DMUs are calculated.

Table 3. Units Classification (1st stage)

Units	Efficiency Scores	Perceived Quality Scores	Classification	Units	Efficiency Scores	Perceived Quality Scores	Classification
DMU1	1.0000	0.9230	HE - HQ	DMU26	1.0000	0.8156	HE - HQ
DMU2	1.0000	0.9304	HE - HQ	DMU27	1.0000	0.8356	HE - HQ
DMU3	1.0000	0.9431	HE - HQ	DMU28	1.0000	0.8007	HE - HQ
DMU4	0.7888	0.8208	LE - HQ	DMU29	1.0000	0.9141	HE - HQ
DMU5	0.7601	0.8600	LE - HQ	DMU30	1.0000	0.9333	HE - HQ
DMU6	0.9899	0.8736	LE - HQ	DMU31	1.0000	0.7793	HE - LQ
DMU7	0.8519	0.8185	LE - HQ	DMU32	1.0000	0.7763	HE - LQ
DMU8	0.6758	0.8704	LE - HQ	DMU33	0.7485	0.7896	LE - LQ
DMU9	0.7066	0.8733	LE - HQ	DMU34	0.8513	0.9342	LE - HQ
DMU10	1.0000	0.8111	HE - HQ	DMU35	1.0000	0.9059	HE - HQ
DMU11	0.7257	0.7815	LE - LQ	DMU36	0.8522	0.8415	HE - HQ
DMU12	1.0000	0.8637	HE - HQ	DMU37	1.0000	0.8234	HE - HQ
DMU13	0.7387	0.7926	LE - LQ	DMU38	1.0000	0.8111	HE - HQ
DMU14	0.9590	0.9689	LE - HQ	DMU39	0.9580	0.8170	LE - HQ
DMU15	1.0000	0.9496	HE - HQ	DMU40	1.0000	0.9607	HE - HQ
DMU16	0.4740	0.9430	LE - HQ	DMU41	1.0000	0.7904	HE - LQ
DMU17	1.0000	0.9037	HE - HQ	DMU42	0.7899	0.7689	LE - LQ
DMU18	0.7125	0.9274	LE - HQ	DMU43	0.6760	0.8459	LE - HQ
DMU19	1.0000	0.9467	HE - HQ	DMU44	0.5890	0.8230	LE - HQ
DMU20	1.0000	0.9452	HE - HQ	DMU45	0.7677	0.8849	LE - HQ
DMU21	1.0000	0.9689	HE - HQ	DMU46	1.0000	0.9467	HE - HQ
DMU22	0.4861	0.8081	LE - HQ	DMU47	0.7546	0.9200	LE - HQ
DMU23	1.0000	0.8076	HE - HQ	DMU48	0.7477	0.9556	LE - HQ
DMU24	1.0000	0.8103	HE - HQ	DMU49	1.0000	0.6659	HE - LQ
DMU25	1.0000	0.8719	HE - HQ	DMU50	1.0000	0.6941	HE - LQ

After the first filtering process, 23 units are regarded as HE-HQ, 5 as HE-LQ, 4 as LE-LQ and 18 as LE-HQ. While HE-LQ units' number is not null, the MQE-DEA formulae should be applied solely to the actual HE-LQ units in order to identify their hypothetical counterparts, thus, the efficiency scores and the levels of the output variables for the five hypothetical units. However, the hypothetical units which replace the actual HE-LQ ones in the sample hold the same perceived-quality - efficiency mix as the actual units located in the LE-HQ segment due to the inverse relationship

underlying the two dimensions of effectiveness.

To be more precise, in case the minimum high-perceived quality level ($q = 0.800$) is selected as the driver to determine the hypothetical units, Formula 4 of the MQE-DEA model is applied in order to calculate the hypothetical efficiency scores. Respecting the basic assumption of the MQE-DEA model, which is the trade-off between perceived-quality and efficiency, the efficiency scores of the hypothetical LE-HQ units are expected to be lower than those of the actual HE-LQ ones regarding quality improvement (Table 4).

Table 4. High-quality adjusted efficiency scores (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 decline in efficiency score of the hypothetical LE-HQ units, while the input levels are fixed, entails a decrease of the outputs produced (i.e. eProtocol services provided, manual services provided and the number of citizens served by every sample CSC) (Table 5). The hypothetical outputs are calculated by applying Formula (9) of the MQE-DEA model.

Table 5. Hypothetical Output Data (2nd stage)

Units	Status	eProtocol Services	Manual Services	Served Citizens
31	A	11764	9721	8769
31	H	11208	9261	8354
32	A	42216	322231	177779
32	H	39947	304910	168223
41	A	16901	62846	16208
41	H	16522	61438	15845
49	A	1699	1015	1483
49	H	1262	754	1102
50	A	3786	1348	2112
50	H	2988	1064	1667

By completing Step 2 of the MQE-DEA algorithm there are no HE-LQ units in the sample under evaluation. Additionally, the outputs of the hypothetical units 31, 32, 41, 49 and 50 replace the outputs of the actual counterpart units in the dataset.

Prior to the application of Step 3 of the MQE-DEA algorithm, output-oriented BCC DEA is run towards a comparative assessment of the production process of the 45 actual and 5 hypothetical units. When the efficiency scores that result from the mathematical formulae of the MQE-DEA model are detached from the DEA comparative evaluation process, it is expected that there will be inconsistency of the

results yielded by the two approaches. The BCC DEA model application specifies the comparative efficiency scores of the mixed actual-hypothetical sample units, and also serves as a cross-validating process to comply with Step 3 of the MQE-DEA algorithm results regarding the units identified as “global” effective with the three “global” best-practice criteria: high-efficiency score ($e = 1.000$), high-perceived quality score ($q \geq 0.800$) and zero-slack production process.

According to the results of the output-oriented BCC DEA model on the actual-hypothetical sample, the efficiency scores of the five hypothetical units are equal to unity. The discrepancy of the five hypothetical units’ efficiency scores yielded by the MQE-DEA mathematical formulae and the BCC DEA model are due to the sensitivity of data in perturbations in case an absolute assessment method and a comparative assessment method are applied. The tolerance of changes in efficiency scores is greater in the latter methods because modifications applied to the production process of a sample unit are compared to the production process of the remaining sample units.

Additionally, changes in efficiency scores, compared to those presented in Table 7, appear in units 2, 12, 21 and 46. After comparative evaluation of the production process of the mixed actual-hypothetical sample units, the four units are deemed low-efficient.

Table 6. BCC DEA Application on quality-adjusted data for sample units' classification

Units	Efficiency Score	Perceived Quality Score	Classification	Units	Efficiency Score	Perceived Quality Score	Classification
1	1.0000	0.9230	(HE-HQ)	26	1.0000	0.8156	(HE-HQ)
2	0.9866	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	0.5357	0.8208	(LE-HQ)	29	1.0000	0.9141	(HE-HQ)
5	0.6795	0.8600	(LE-HQ)	30	1.0000	0.9333	(HE-HQ)
6	0.8908	0.8736	(LE-HQ)	31	1.0000	0.8000	(HE-HQ)
7	0.8799	0.8185	(LE-HQ)	32	1.0000	0.8000	(HE-HQ)
8	0.6221	0.8704	(LE-HQ)	33	0.2541	0.7896	(LE-LQ)
9	0.7063	0.8733	(LE-HQ)	34	0.4172	0.9342	(LE-HQ)
10	1.0000	0.8111	(HE-HQ)	35	1.0000	0.9059	(HE-HQ)
11	0.3473	0.7815	(LE-LQ)	36	0.6493	0.8415	(LE-HQ)
12	0.5278	0.8637	(LE-HQ)	37	1.0000	0.8234	(HE-HQ)
13	0.5725	0.7926	(LE-LQ)	38	1.0000	0.8111	(HE-HQ)
14	0.9782	0.9689	(LE-HQ)	39	0.9580	0.8170	(LE-HQ)
15	1.0000	0.9496	(HE-HQ)	40	1.0000	0.9607	(HE-HQ)
16	0.2767	0.9430	(LE-HQ)	41	1.0000	0.8000	(HE-HQ)
17	1.0000	0.9037	(HE-HQ)	42	0.3405	0.7689	(LE-LQ)
18	0.6005	0.9274	(LE-HQ)	43	0.6463	0.8459	(LE-HQ)
19	1.0000	0.9467	(HE-HQ)	44	0.2107	0.8230	(LE-HQ)
20	1.0000	0.9452	(HE-HQ)	45	0.6990	0.8849	(LE-HQ)
21	0.5070	0.9689	(LE-HQ)	46	0.6882	0.9467	(LE-HQ)
22	0.4905	0.8081	(LE-HQ)	47	0.5352	0.9200	(LE-HQ)
23	1.0000	0.8076	(HE-HQ)	48	0.6477	0.9556	(LE-HQ)
24	1.0000	0.8103	(HE-HQ)	49	1.0000	0.8000	(HE-HQ)
25	1.0000	0.8719	(HE-HQ)	50	1.0000	0.8000	(HE-HQ)

Returning to Step 3 of the MQE-DEA algorithm, three best-practice reference sets are uncovered. Level 1 stands for the “global” reference set and the remaining levels are intermediate frontiers (Table 7). The five quality-driven – efficiency-adjusted operational units (i.e. units: 31, 32, 41, 49 and 50) are located in the “global” reference set;

while they meet all the effectiveness criteria, as it is also validated by the BCC DEA model results (Table 6) as well as by Table 6B in the Appendices. In the latter Table, units 31, 32, 41, 49 and 50 are referenced by themselves proving the lack of slacks in their production process.

Table 7. Sample partition into multilevel reference sets

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

A paradox of the Step 3 application, which relaxes the sample units' effectiveness classification to the Context-dependent DEA model, is the identification of units 14 and 21 as highest-level benchmarks. The former received an efficiency score lower than unity at Step 1 of the MQE-DEA algorithm application (Table 3) and at the cross-validating process of the BCC DEA application (Table 6). The latter unit (unit 21) is regarded as low-efficient based on the outputs of the BCC DEA model (Table 6), though the Step 1 results classified it in the HE-HQ group.

This paradox seems to be a flaw of the Context-dependent DEA model that shows up when output-oriented variable returns to scale approach is applied. In a previous study, put forth by Brissimis and Zervopoulos (2011), input variables of the same dataset as that used in the current study were modified to attain high-perceived quality standards. Application

of the input-oriented variable returns to scale Context-dependent DEA model did not lead to such an inconsistency. In fact, the results obtained by the Step 3 of the MQE-DEA algorithm were in line with the cross-validating BCC DEA results.

The feasibility of the outputs yielded by the MQE-DEA method in the short-run, compared to those of a traditional DEA method, becomes explicit in Table 8. While the sample units are clustered into three levels, according to the MQE-DEA analysis, unit 8, located in Level 3, provides a gradual improvement path, first to Level 2 and then from Level 2 to Level 1. The aggregated changes, suggested by the MQE-DEA analysis, towards "global" effectiveness are smoother than those yielded by the traditional BCC DEA model application. In the BCC DEA case, unit 8 is expected to "take-off" at once in order to reach the best-practice frontier.

Table 8. Feasible Targets Identification (Progress Potentials)

Steps	CurrentStatus (Unit/Level)	Evaluation Context (Level)	TargetOutputs / (% Change)		
			eProtocolServices	ManualServices	ServedCitizens
1	Unit 8/Level 3	Level 1	22048 (+60.7%)	30968 (+181.4%)	27760 (+101.0%)
1	Unit 8/Level 3	Level 2	16238 (+18.4%)	13663 (+24.2%)	16368 (+18.5%)
2	Unit 8/Level 2	Level 1	22048 (+35.8%)	30968 (+126.7%)	27760 (+69.6%)

6. CONCLUSION AND FURTHER RESEARCH

This paper introduces a “rational” short-term effectiveness assessment methodology that is particularly applicable in case an inverse relationship appears between the dimensions of effectiveness. The developed MQE-DEA model is output-oriented in order to relax input disposability restrictions, such as protectionism over the resources engaged, which commonly are experienced in public organizations.

The aim of the MQE-DEA model is the identification of the comparative maximum outputs which should be produced by every non-best-practice unit, holding the input levels fixed while taking into account, at the same time, the provision of high quality standards based on customers’ or citizens’ perception. To select a best-practice operational unit, all the high efficiency, high quality and zero-slack production process criteria should be met. Although best-practice units are perceived solely as the “global” reference units, the MQE-DEA model sets local reference units that act as intermediate or short-term targets for the lower effectiveness level units. By introducing short-term targets, a customized step-by-step path for improvement can be traced for every disqualified sample unit based on comparative assessment.

The output-oriented MQE-DEA model could be extended by applying its properties in cases in which non-discretionary output variables exist. Further analysis is needed in multi-dimensional settings where more than two variables determine effectiveness. Another field which could be explored is the generalization of the model yielding results that take into account population and not sample data.

References

1. Banker, R., Charnes, A. and Cooper, W.W. (1984) Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis, *Management Science* 30 (9): 1078-1092.
2. Bessent, A., Bessent, W., Elam, J. and Long, D. (1984) Educational Productivity Council Employs Management Science Methods to Improve Educational Quality, *Interfaces* 14 (6).
3. Brissimis, S.N. and Zervopoulos, P. (2011) Developing a Step-by-Step Effectiveness Assessment Model for Customer-Oriented Service Organizations, *MPRA Paper 30765*, University Library of Munich.
4. Charnes, A., Cooper, W.W. and Rhodes, E. (1978) Measuring Efficiency of Decision Making Units, *European Journal of Operational Research* 2: 429-444.
5. Chilingirian, J. and Sherman, D. (1990) Managing Physician Efficient and Effectiveness in Providing Hospital Services, *Health Service Management Research* 3 (1): 3-15.
6. De Bruijn, H. (2007) *Managing Performance in the Public Sector* (2nd ed.). Routledge, Oxon, UK.
7. Paradi, J., Vela, S. and Yang, Z. (2004) *Assessing Bank and Bank Branch Performance: Modeling Considerations and Approaches*, cited in Cooper, W., Seiford, L. and Zhu, J., *Handbook on Data Envelopment Analysis*. Kluwer Academic Publishers, London, UK: 349-400.
8. Seiford, L.M. and Zhu, J. (2003) Context-Dependent Data Envelopment Analysis: Measuring Attractiveness and Progress, *OMEGA* 31 (5): 397-480.
9. Sherman, D. and Zhu, J. (2006) Benchmarking with Quality-Adjusted DEA (Q-DEA) to Seek Lower-Cost High-Quality Service: Evidence from a U.S. Bank Application, *Annals of Operations Research* 145: 301-319.
10. Soteriou, A. and Zenios, S.A. (1999) Operations, Quality and Profitability in the Provision of Banking Services, *Management Science* 45 (9): 1221-1238.
11. Zervopoulos, P. and Palaskas, T. (forthcoming) Applying Quality-Driven, Efficiency-Adjusted DEA (QE-DEA) in the Pursuit of High-Efficiency – High-Quality Service Units: An Input-Oriented Approach. *IMA Journal of Management Mathematics* (DEA special issue)

APPENDIX

SECTION 1

Equation (3) can be rewritten as:

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

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

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

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

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

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

The first critical value:

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

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

On the contrary, the alternative critical value:

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

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

The generalized formula is the following:

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

SECTION 2

Equation (8)

$$e' = \frac{\sum_{r=1}^s u_r y_r'}{\sum_{i=1}^m v_i x_i} \quad (\text{multiplying both sides by } \frac{1}{e'})$$

where $e' \neq 0$)

$$1 = \frac{\sum_{r=1}^s u_r y_r'}{e' \sum_{i=1}^m v_i x_i} \quad (8a)$$

Introducing (8a) to equation (7), results:

$$\sum_{r=1}^s u_r y_r' = e' \sum_{r=1}^s u_r y_r' \quad (8b)$$

Equation (8b) leads to the hypothetical output determination formula:

$$\left. \begin{aligned} y_1' &= e' y_1 \\ y_2' &= e' y_2 \\ \dots & \\ y_s' &= e' y_s \end{aligned} \right\} \quad (9)$$