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Evaluating shops efficiency using data envelopment analysis: Categorical approach*

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Abstract

The article introduces Data Envelopment Analysis (DEA) and its applicability as mathematical programming technique. It evaluates the performance of homogeneous operating decision-making units. DEA has been proven as valuable performance evaluation method in situations when decision-making units under consideration have multiple inputs and outputs and operate under similar conditions. For dealing with situations when units operate under different conditions, we have proposed categorical approach and analysed the influence of unit's environment on relative efficiency results by applying categorical model on real data of 57 shops within one retailing organization. DEA identified good operating practices as members of efficient frontier (benchmark members) and those under efficient frontier that should be analysed as candidates for reorganization or even closure. Relative efficiency results obtained by non-controllable BCC model and categorical BCC model were significantly different so our conclusion is that business environment greatly influences the performance evaluation for several units and should be additionally investigated.

Key words: *data envelopment analysis, BCC model, retailing, categorical variables*

***JEL classification**: C44, C61*

1. Introduction

Dynamic environment in which decision-making units operate and the opportunities to remain competitive in the market make evaluating business performance the top priority for managers. The usual measures of efficiency as a ratio form output/input are inadequate and there is not a well-defined production function where a given set

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of known inputs can be expected to yield a predictable output. Managers are realizing that technology and information can create competitive advantages by improving efficiency, increasing profits, and/or reducing costs.

Recent years have seen a great variety of applications of DEA for evaluating the performances of different kinds of entities in different kind of activities (Cooper, Seiford, Tone, 1999). There is a growing body of literature supporting DEA as a “provocative and insightful methodology for evaluating organizational performance and establishing benchmarking practices for many different applications” (Thomas, 1994:27). There are empirical evidences in different area studies to support that the DEA efficiency metric is good enough to use it as valuable managerial judgement tool. We will present some of them:

The set of bank branches was analysed by CAR-DEA model (Cook and Zhu, 2008) and the performance evaluation was obtained by capturing more accurately the circumstances in which the decision-making units (DMU) operate. The assurance regions constraints were imposed by considering environmental circumstances of bank branches, which resulted as more rational performance evaluation.

Goal programming constraints were added to DEA model in order to improve its accuracy (Cook et al., 2007) and DEA scores computed with these restricted DEA models were more consistent with bank management classification.

The impact of merger and acquisition on banking efficiency was also investigated within DEA framework (Weiguo et al.). The analysis found merger and acquisition had greater impact on banking efficiency of Chinese banks than that of American banks and the authors gave some suggestion for Chinese banking industry to improve the banking efficiency.

The cost-efficiency of research programs in economics and business management faculties of Dutch universities was examined by DEA. (Cherchye et al., 2008). The application shows that proposed methodology may entail robust conclusions regarding cost-efficiency differences between universities within specific specialization areas. Such insights may be particularly useful for benchmarking purposes.

DEA was used in allocative efficiency evaluation on dairy farms in Sweden (Hansson, 2007). The results show indicators of economic performance and contribute to improving decision-making at the farms and thus leading to more sustainable farms.

An empirical investigation of contributing factors to information technology investment utilization in transition economies was conducted by DEA combined with decision trees and cluster analysis in the context of 18 transition economies (Samoilenko, 2008). Use of DEA allowed to determining the relative efficiency of the utilization of investments by each transition economy in the sample.

One of the main characteristic of DEA is flexibility in selecting the factor weights which deters the comparison among DMUs on a common base. In order to deal with this difficulty multi-objective linear programming approach for generating common set of weights under DEA framework is proposed (Makui et al., 2008). To illustrate the idea of the proposed approach, 17 forest districts (DMUs) were evaluated by DEA (BCC model).

Similar, a multi-criteria DEA model used in literature to moderate the homogeneity of weight dispersion is solved using pre-emptive goal programming (Bal et al., 2007).

A DEA model of environmental efficiency using indicators of fossil fuels utilization, emissions rate and electric power losses is presented and dynamics of environmental efficiency is analysed (Vaninsky, 2008). Due to its nonparametric nature, DEA has been proposed as appropriate methodology for analysing environmental efficiency of the electric industry of the United States.

DEA and SFA approaches were combined to conduct the efficiency rankings of health care foodservice operations (Matawie et al.,2008).

One reason is that DEA has opened up possibilities for use in cases where the other approaches could not because of the complex or unknown relations between multiple inputs and outputs. Namely DEA is nonparametric technique and does not presume any functional form of converting inputs into outputs, which is an important advantage comparing to parametric techniques. Furthermore, the linear and mathematical programming models and methods used in DEA effect their evaluations from observed performances. This is in contrast to the usual averaging as it is common in statistic or accounting. DEA also identify the sources and amounts of inefficiency in each input and each output for every entity and provide an efficiency measure for each entity or activity of interest.

Management of the organization may have already a perception as to classification of its unities as good and poor performers. Such perceptions may emerge from observations that lie beyond the scope of the available quantitative data. Data Envelopment Analysis is one of the methods, which we can use to assess the comparative efficiency of homogeneous operating units. It is a potentially valuable management information methodology for business performance in a complex environment. DEA as quantitative technique that mathematically derives the utilization efficiency of unit's use of inputs (resources) relative to produced outputs (outcomes) offers a quantitative measure of a firm's success at "market-engineering" while providing internal benchmarking opportunities to assist large organizations in improving their core processes and overall performance.

2. Methodology

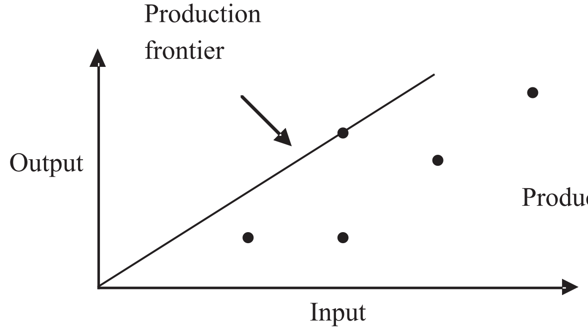
The resource allocation is the fundamental concept governing mathematical programming. DEA is mathematical programming method initially developed for assessing the comparative efficiencies of organisational units (like bank branches, shops, hospitals and other instances where units perform similar tasks), which utilise similar "inputs" to "produce" similar "outputs". Inputs (resources) and outputs (outcomes) should be relevant for process estimation. DEA is non-parametric methodology and does not presume any functional form linking inputs to outputs. Instead, we attempt to construct a production possibility set from the observed input-output correspondences at the assessed units.

Suppose there are n decision making units: DMU_1, DMU_2,..., DMU_n converting inputs in outputs. If we select m inputs and s outputs for DMU_j then the input and output data can be represented as: (x_{1j}, x_{2j},..., x_{jn}) and (y_{1j}, y_{2j},..., y_{jn}). Given the data, we measure the efficiency of each DMU once and hence need n optimisations for each DMU_j to be evaluated. We solve the linear programming problem to obtain values for the input "weights" and output "weights" which are derived from the data instead of being fixed. Mahajan (1991) suggest DEA when we consider individual DMU, relative to other similar DMUs. It is useful as a tool for resources allocation and benchmarking because of real (not normative) goals that efficient units achieved.

2.1. CCR model

One of the basic DEA models is CCR model named by initials of its authors Charnes, Cooper and Rhodes. The model is built on the assumption of constant returns to scale of activities. It means that if an activity *(x,y)* is feasible, then, for every positive scalar *t*, the activity *(tx,ty)* is also feasible. The efficient production frontiers have constant returns-to-scale characteristic, as depicted figure 1.

Figure 1: Production Frontier of the CCR Model



Source: Cooper W. et al. (2000:86)

The idea of the model is as follows: for each DMU we form the virtual input and output by input weights (v_i) ($i = 1,...,m$) and output weights (u_r) ($r = 1,..., s$). Then we use following fractional programming to maximize the ratio virtual output/virtual input (Cooper et al.,1999:23) .

$$\max \qquad \theta = \frac{u_1 y_{10} + u_2 y_{20} + ... + u_s y_{s0}}{v_1 x_{10} + v_2 x_{20} + ... + v_m x_{m0}}$$

$$\text{subject to} \qquad \frac{u_1 y_{1j} + ... + u_s y_{sj}}{v_1 x_{1j} + ... + v_m x_{mj}} \leq 1 \ (j = 1,..., n)$$

$$v_1, v_2, ..., v_m \geq 0$$

$$u_1, u_2, ..., u_s \geq 0$$

The above fractional program is equivalent to the following linear program:

$$\max \qquad \theta = \mu_1 y_{10} + ... + \mu_s y_{s0}$$

$$\text{subject to} \qquad \upsilon_1 x_{10} + ... + \upsilon_m x_{m0} = 1$$

$$\mu_1 y_{1j} + ... + \mu_s y_{sj} \leq v_1 x_{1j} + ... + v_m x_{mj} \ \ (j = 1,..., n)$$

$$\upsilon_1, \upsilon_2, ..., \upsilon_m \geq 0$$

$$\mu_1, \mu_2, ..., \mu_s \geq 0$$

The optimal solution of a linear program is now represented by (θ^*, v^*, u^*) and the CCR-Efficiency can be explained as (Cooper et al.,1999:24)

Definition (CCR- Efficiency:)

DMU_0 is *CCR-efficient if* $\theta^* = 1$ *and there exists at least one optimal* (v^*, u^*) *with* $v^* > 0$, $u^* > 0$.

*Otherwise, DMU_0 is CCR-inefficient***.**

The subset E_0 composed of CCR-efficient DMUs is called *the reference* set or the *peer group* to the *DMU_0*. The set spanned by E_0 is called the *efficient frontier* of *DMU_0*.

2.2. BCC model

The BCC model evaluates the efficiency of DMU_0 (0 = 1, ...,n) by solving the following linear program (Cooper et al.,1999:88)**:**

$$
\begin{array}{ll}
(BCC_0) & \min \theta_B \\
\text{subject to} & \theta_B x_0 - X\lambda \geq 0 \\
 & Y\lambda \geq y_0 \\
 & e\lambda = 1 \\
 & \lambda \geq 0
\end{array}
$$

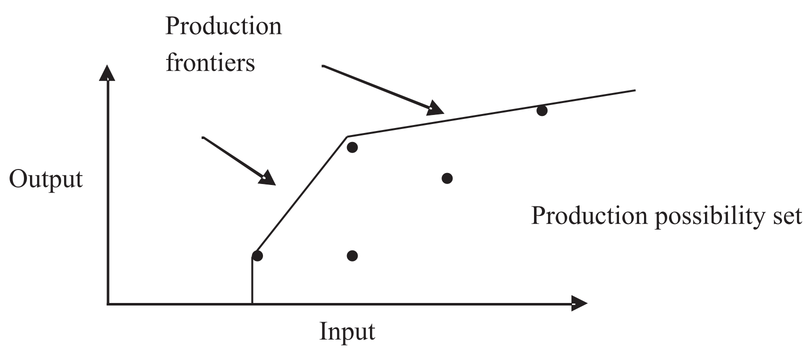
where θ_B is scalar.

The dual form of a linear program (BCC_0) is:

$$
\begin{array}{ll}
\max & z = uy_0 - u_0 \\
\text{subject to} & vx_0 = 1 \\
 & -vX + uY - u_0 e \leq 0 \\
 & v \geq 0,\ u \geq 0,\ u_0 \text{ is free in sign}
\end{array}
$$

BCC model has its production frontiers spanned by the convex hull of the existing DMUs. The frontier has piece-wise linear and concave characteristics which leads to variable returns-to-scale characterizations.

Figure 2: Production Frontier of the BCC Model



Source: Cooper W. et al. (2000:86)

Definition (BCC - Efficiency)(Cooper et al.,1999:89)

If an optimal solution $(\theta_B, \lambda^*, s^{-*}, s^{+*})$ *for* (BCC_0) *satisfies* $\theta_B^* = 1$ *and has no slack* $(s^{-*} = 0, s^{+*} = 0)$, *the* D_0 *is then called BCC-efficient, otherwise it is BCC-inefficient.*

Slacks s^{-*} and s^{+*} represent the maximal input excesses and output shortfalls, respectively. In the first phase of solving the primal problem, we minimize θ_B and, in the second phase, we maximize the sum of the input excesses and output shortfalls, keeping $\theta_B = \theta_B^*$ (the optimal objective value).

Definition (Reference Set):(Cooper et al., 1999:89)

For a BCC-inefficient D_0 *we define its reference set* E_0, *based on an optimal solution* λ^* *by:*

$$E_0 = \{j \mid \lambda^*_j > 0\} \ (j \in \{1, ..., n\})$$

″In case of multiple optimal solutions, any solution chosen satisfies the following

$$\theta^*_B x_o = \sum_{j \in E_o} \lambda^*_j x_j + s^{-*}$$

$$y_o = \sum_{j \in E_o} \lambda^*_j y_j - s^{+*}$$

that leads to the formula for improvement, which is called the BCC-projection (Cooper et al.,1999:90):

$$\hat{x}_o \Leftarrow \theta^*_B x_o - s^{-*}$$

$$\hat{y}_o \Leftarrow y_o + s^{+*}$$

2.3. Incorporating value judgements in DEA assessments

Managerial judgement in determining the resources necessary to produce the desired performance outcomes is very important. Koutsoukis and Mitra (2004:5) pointed that managers were charged with the responsibility of:

1. *Forecasting and planning*: That is to assess the future and make provision for it in unity with an organisation's goals.
2. *Organising*: to build up an organisation in terms of its material and human structure that will allow the basic activities to be performed in the best possible way for the benefit of the organisation.
3. *Commanding*: the organisation must be set in motion and activity should be maintained. Through their capacity to command, managers can obtain the best possible performance from their subordinates.

4. *Coordinating*: the activity of any organisational unit should be consistent with the activities of other units and overall the units should be kept in perspective to the organisation's overall aims and objectives.
5. *Controlling*: this element is used to check if the other four elements are performing properly.

That is, during the repeated modelling and solving cycle analysts and decision makers alike, seek to understand the behaviour of the system. DEA models with inputs and outputs defined using expert knowledge are more likely to accept the computed measures, and consultants use them as managerial tools. In some settings management opinion as to performance status of a DMU can be misdirected. This may result when management is focused on only one component of an operation and fails to take full consideration of all aspects of performance. However, consultant knowledge must be treated as being more than "opinion" (Bala and Cook, 2003:443) . It follows that DEA models with inputs and outputs defined using expert knowledge are more likely to accept the computed measures, and consultants can use them as managerial tools.

3. Analysis

As illustration of DEA application in evaluation multi-units organization performance we have selected a large retailing organization consisting of 57 shops. First and crucial step is the selection of some common inputs and outputs that reflect the analyst's interest. There are no restrictions in selection of inputs and outputs, but smaller input amounts and larger output amounts are preferable. One of the basic and very important features of DEA methodology is that measurement units of the different inputs and outputs do not need to be congruent. (Some may involve number of persons, or areas of floor space etc.)

3.1.Inputs and outputs selection

The right choice of adequate inputs and outputs is one of the difficult steps in the DEA utilization. In the first stage the executive management has identified 7 inputs and 3 outputs as measures of operational efficiency for evaluating a sample of 57 shops.

a) Inputs:

1. *Supplying value of goods* is selected as the value that presents the basic input. It has the significant influence on the price formatting.
2. *The average number of full-time employees* is very important input because of its influence on customer's behaviour and also on shop image and quality perception.

Comparing to part-time employees, full-time employees tend to be better informed, have more experience and are more effective in generating sales.

3. *The area of selling space* is important indicator of selling capabilities.
4. *Average inventory level* is the measure of internal business process effectiveness. The more inventory the greater management's expectations of profits.
5. *The number of cash registers* as the indicator of potential customers.
6. *The labour costs* are the measure of professional abilities.
7. *Other operating expenses* are all costs, except labour costs.

b) Outputs:

1. *Sales* as the indicator of business results
2. *Realised margin value* **a**s the indicator of business results.
3. *Profit* as one of the most important business outcome and measure of efficiency.

After inputs and outputs selection[2], we decided to exclude the number of cash registers from analysis because almost 50% of shops had only 1 cash register. This fact could influent the efficiency analysis result because some shops could be evaluated as efficient only because of minimum value of this input. So, now we selected 6 inputs and 3 outputs as relevant to our analysis.

3.2. Types of inputs and outputs

Inputs and outputs should be now classified as controllable and non-controllable. Controllable are those, which are under the control of organisational management and non-controllable are those on which management cannot influence. Typical example of non-controllable input is the area of selling space[3] and management agreed that this should be taken into account. The others inputs and outputs were considered as controllable.

3.3. Assurance region constraints

The next step was deciding whether to include assurance region constraints or not. Namely, as we mentioned before in DEA input "weights" and output "weights" are derived from the data instead of being fixed. It means that DEA uses variable weights, which are chosen in a manner that assigns a best set of weight to each evaluated unit.

[2] Some of these inputs and outputs are already used before in technical efficiency estimating of 12 shops.

[3] Maybe we could change the area of selling space in long term, but in short term it is fixed

But sometimes we want to have some sort of "control" over the efficiency result. Namely, management think that some inputs and outputs are more important then the others and relative efficient shops should be assessed due to those more important. So, we decided to incorporate in DEA model assurance region constraints that make a sharper discrimination among DMUs possible. The weights constraint can be then applied within inputs or within outputs and cannot be applied between inputs and outputs. The name *assurance region* (AR) comes from constraint, which limits the region of weights to some special area. By the additions of these constraints, DMU previously evaluated as efficient may be found to be inefficient. Organisational management have decided that constraints, should be on all outputs and one opinion was that profit should be constrained to 60%, margin value to 20% and sales to 20% of total efficiency results. The other opinion was that these parts should be 50%, 30 % and 20 %. We assigned upper and lower assurance region constraints which was affecting the objectivity of analysis but also necessary to do because profit should have the greatest influence on relative efficiency result.

3.4. Model-type selection

The next step was model-type selection. We could not identify the characteristics of the production frontiers and it was risky to rely on only one particular model. That is why in the second stage, the basic CCR model and BCC model were applied to derive a performance measure for each shop and the relative efficiency results were obtained. Table1 displays summaries of the experiments of two models. Because of significant differences between the results obtained by CCR (13 efficient shops) and BCC model (19 efficient shops) we concluded that variable returns-to-scale characterisation (BCC type of model) is more appropriate than constant returns-to-scale characterisation (CCR).

Table 1: Statistic by CCR and BCC Model

Result of analysis	CCR score	BCC score
No. of efficient shops	13	19
No. of inefficient shops	44	38
Average efficiency result	0.976	0.982
Standard deviation	0.027	0.027
Maximum efficiency result	1	1
Minimum efficiency result	0.880	0.890

Source: Author's calculations

3.5. Model orientation

Now when we selected BCC model as more appropriate model we could continue to investigate if BCC model should be input or output oriented. “Oriented”, indicates the input or output orientation in evaluating efficiency, i.e. the main target of evaluation is either input reduction or output expansion. There are three directions, one called input-oriented that aims at reducing the input amounts by as much as possible while keeping at least the present output levels, and the other, called output-oriented, maximizes output levels under at most the present input consumption. Other models that deal with the input excesses and output shortfalls simultaneously represent the third choice. We decided to select BCC model with input-orientation because of possibility to investigate how much should we reduce inputs to achieve the present level of outputs Input-oriented BCC model has also very important feature: it is translation invariant with respect to outputs (but not inputs). It means that it evaluate the efficiency of a DMU by l_1 – metric distance from the efficient frontiers and are invariant with respect to the translation of the coordinate system. DEA model is translation invariant if translating the original input and/or output values results in new problem that has the same optimal solution for the envelopment form as the old one. This allowed us to include in analysis shops with llosses.

4. Results of analysis

4.1. Relative efficiency results

In the next stage BCC non-controllable, input-oriented model was applied to derive a performance measure for each shop and the relative efficiency results were obtained. Table 2 displays statistics of the relative efficiency results for 57 shops. As we can see, the assumption of non-controllable selling area space affected significantly the efficiency results. It means that selling space for 14 shops (33-19) could be too expensive as input or eventually not used, as it should be.

Table 2: Statistic of Non-controllable BCC Score

Result of analysis	BCC score
No. of efficient shops	33
No. of inefficient shops	24
Average efficiency result	0.989
Standard deviation	0.021
Maximum efficiency result	1
Minimum efficiency result	0.905

Source: Author’s calculations

The summary of relative efficiency results obtained by BCC input oriented model with constraints for assurance region are displayed in table 3. We can conclude that only 1 shop (19-18) (before assessed as relative efficient) with the constraints for assurance region became relative inefficient. It could mean that almost all shops evaluated as efficient have been evaluated as efficient mostly on the base of realized profit.

Table 3: Statistic of BCC Score with Constraints for Assurance Region

Result of analysis	BCC score
No. of efficient shops	18
No. of inefficient shops	39
Average efficiency result	0.897
Standard deviation	0.110
Maximum efficiency result	1
Minimum efficiency result	0.581

Surce: Author's calculations

Those shops which were relative efficient in both cases could be referred as better performers, but not the best. How to distinguish the best of them? One of the possibilities to do that is to investigate the reference set frequency (for all efficient shops) as the indicator of the "best performer". When doing this it is important to look for an efficient unit with the most similar input/output characteristic to the inefficient units (Banxia Frontier Analyst Case Study). Table 4 displays the frequency in reference set for efficient shops.

Table 4: The Reference Set Frequency

Shop	Reference set frequency	Shop	Reference set frequency
1	3	10	0
2	0	11	3
3	4	12	0
4	0	13	12
5	24	14	0
6	0	15	3
7	0	16	0
8	5	17	1
9	33	18	1

Source: Author's calculations

We can see that shop 9 (with reference set frequency equal to 33) is candidate for "best performer" within 18 efficient units. Thanassoulis (2002) pointed that further detailed analysis and possibly inspection of the worst and the best performers is then necessary in order to understand the production process and derive useful information which may help both the worst and the best performers to make improvements in efficiency.

4.2. Sources and the amounts of relative inefficiency

In the next stage the sources and the amounts of relative inefficiency were identified for each of 39 inefficient shops. Table 5 displays the projection values for one of it. Differences between actual data and projected values show how much inefficient shop needs to reduce its inputs in order to become efficient relative to efficient shop in his reference set.

Table 5: The Potential Improvements (Projection values)

Inputs	Data	Projection	Difference	Percent
Supplying value of goods	789,699.00 kn	698,522.70 kn	-91,176.30	-11.55
The average number of full-time employees	3	2	-1	-33.33
The area of selling space	105 m^2	83.71 m^2	-21.29	-20.27
Average inventory level	108,539.00 kn	46,606.60 kn	-61,932.40	-57.06
The labour costs	72,973.00 kn	55,285.80 kn	-17,687.20	-24.24
Oper. expenses	106,019.00 kn	52,938.50 kn	-53,080.50	-50.07

Source: Author's calculations

Selected shop should reduce all of its inputs to become efficient, comparing to other shops, especially the average level of inventory (for 57.06 %) and operating expenses (for 50.07 %). This provides an additional opportunity for inefficient shops to focus on how much to improve some of their properties in order to be efficient. As we noted in paragraph 3.5, we were interested in input reduction: we could also consider output maximizing under at most the present input consumption.

4.3. Benchmark members

The next step was to consider shops that achieved relative efficiency by three types of model: BCC input-oriented model without any assumptions, BCC input oriented model under assumptions of non-controllability of selling space and BCC input oriented model with output constraints for assurance region. Table 6 displays relative efficiency results by three different models.

Table 6: Relative efficiency results: three types of models

Result of analysis	BCC, Non-controllability, Assurance region score
No. of efficient shops	18
No. of inefficient shops	39

Source: Author's calculations

Eighteen shops of set of fifty-seven included in analysis are evaluated as relative efficient by three different types of models, involving the expert knowledge. These efficiency results were more in line with management beliefs and those eighteen shops could be benchmark members.

4.4. Categorical approach

Till now we evaluated shops without estimating the sales environment. Our evaluation has been unfair to the shops in the high competitive situation. Management was very interested in considering the influence of shop's location on relative efficiency results.

Such situation is possible to handle with categorical DMUs. We classified shops at best locations in category 3, shops at better locations in category 2 and shops at worst locations in category 1 (Cooper et al., 1999). Then we evaluate shops in category 1 only within the group, shops in category 2 with reference to shops in category 1 and 2 and shops in category 3 within all shops in the model. It means that shops in the upper categories cannot be chosen as basic variables for shops in the lower category. Categorical BCC input-oriented model was applied to derive a performance measure for each shop and the relative efficiency results were obtained. The results of analysis based on this categorization are given in table 7. Statistic by category is displayed in table 8.

Table 7: Statistic by BCC Categorical Model Score

Result of analysis	BCC categorical model score
No. of efficient shops	30
No. of inefficient shops	27
Average efficiency result	0.990
Standard deviation	0.022
Maximum efficiency result	1
Minimum efficiency result	0.897

Source: Author's calculations

Table 8: Statistic by Category

Result of analysis	Category 1	Category 2	Category 3
No. of DMU	20	17	20
No. of efficient DMU	11	8	11
No. of inefficient DMU	9	9	9
Average efficiency result	0.996	0.974	0.997
Standard deviation	0.007	0.034	0.004
Maximum efficiency result	1	1	1
Minimum efficiency result	0.976	0.897	0.986

Source: Author's calculations

As we expected, categorical approach made great differences in relative efficiency comparing to previous efficiency results. We evaluated shops under "handicaps", taking into account their particular environments. Shops, which were evaluated as relative efficient in all cases, could be considered as the candidates for best performers. This kind of information can be taken into account by higher management for instance in assigning bonuses, based on actual performance. Theirs reference set frequencies are displayed in table 9.

Table 9: The Reference Set Frequency

Shop	Reference set frequency	Shop	Reference set frequency
1	2	16	10
2	1	17	2
3	3	18	11
4	3	19	6
5	4	20	2
6	2	21	9
7	0	22	0
8	0	23	1
9	1	24	0
10	0	25	7
11	7	26	0
12	6	27	2
13	2	28	1
14	2	29	2
15	0	30	2

Source: Author's calculations

Shops number 18 and 16 with reference set frequencies 11 and 10 are the candidates for best performers and should be considered with special care.

Shops, which were evaluated as relative inefficient in all cases, could be considered as potential candidates for reorganization or closure, in the worst case. The others, which were evaluated as efficient by one and inefficient by another model, should be considered with special care and additional investigation is then necessary.

The table 10 displays potential improvements (projection values) for the same shop as before (see table 5) but now under categorical approach. We can see that differences between actual data and their projection values are now smaller for all inputs except the average number of full time employees. It means that projection values are easier to achieve for all shops evaluated as inefficient by categorical BCC input-oriented model.

Table10: The Potential Improvements (Projection Values)

Inputs	Data	Projection	Difference	Percent
Supplying value of goods	789,699.00 kn	784,581.60 kn	-5,117.37	-0.65
The average number of full-time employees	3	2	-1	-33.33
The area of selling space	105.00 m^2	90.15 m^2	-14.85	-14.15
Average inventory level	108,539.00 kn	54,527.85 kn	-54,011.15	-49.76
The labour costs	72,973.00 kn	60,136.41 kn	-12,836.59	-17.59
Oper.expenses	106,019.00 kn	58,427.99 kn	-47,591.01	-44.89

Source: Author's calculations

5. Conclusion

DEA has been proven as valuable performance evaluation method when homogeneous decision-making units under consideration have multiple inputs and outputs and operate in similar conditions. It identified the best performers among them and helped managers answer the question not only how well are the units doing but also how much could they improve through projected values. The problem arises when we compare the performance of DMUs operating under different conditions because of rationality in proposals for improvement or unit's reorganisation. We proposed the solution of this problem by adopting categorical approach in analysis and applying categorical model which improved the evaluation of DMUs performance. To be specific: relative efficiency results obtained by non-controllable BCC model and categorical BCC model were significantly different so we concluded that business environment greatly influenced on relative efficiency results in several units. Furthermore, analysis identified two units, which are performing best, and their operating practices can be examined to establish a guide to best practice. Of course, there are some limitations of our analysis: it is conducted on the base of past data and we have dealt with DEA utilization under static conditions. This can be misleading since dynamic settings may give rise to seemingly excessive use of resources, which produce beneficial results in future periods. The analysis can be improved by time-dependent use of DEA called window analysis. The basic idea is to regard each DMU as if it were different DMU in each of reporting dates.

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Ocjena efikasnosti trgovina primjenom analize omeđivanja podataka: kategorijski pristup

Alemka Šegota[1]

Sažetak

Članak predstavlja analizu omeđivanja podataka (AOMP) i njezinu primjenjivost kao tehnike matematčkog programiranja koja ocjenjuje rezultate rada homogenih jedinica koje donose odluke. AOMP se dokazala kao korisna metoda ocjene rezultata rada u situacijama kada jedinice koje donose odluke koje razmatramo imaju višestruke inpute i outpute i rade u sličnim uvjetima. U slučajevima kada jedinice rade u različitim uvjetima predložili smo kategorijski pristup: primijenili smo kategorijski model i analizirali utjecaj okoline jedinice na njezin rezultat efikasnosti primjenom modela na stvarne podatke za 57 trgovina jednog maloprodajnog lanca. AOMP je identificirala jedinice dobre prakse kao članove efikasne granice kao i one jedinice koje se nalaze ispod granice efikasnosti i trebale bi se analizirati kao kandidati za reorganiziranje ili čak zatvaranje. Rezultati relativne efikasnosti dobiveni ne-kontrolabilnim BCC modelom i kategorijskim BCC modelom su se znatno razlikovali pa smo zaključili da poslovna okolina znatno utječe na ocjenu rada određenih jedinica koje zbog toga treba dodatno analizirati.

Ključne riječi: *analiza omeđivanja podataka, BCC model, maloprodaja, kategorijske varijable*

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