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WPŁYW NAKŁADÓW NIEDECYZYJNYCH NA OCENĘ EFEKTYWNOŚCI ZARZĄDZANIA KRYZYSOWEGO Z WYKORZYSTANIEM DEA

Streszczenie. Celem artykułu jest ocena wpływu uwzględnienia nakładów niedecyzyjnych na wyniki pomiaru efektywności zarządzania kryzysowego. Badanie przeprowadzono na przykładzie reakcji wybranych państw na pandemię COVID-19 w pierwszych 60 dniach od przekroczenia progu 100 potwierdzonych przypadków zakażeń. Porównano cztery warianty modeli DEA: CCR, CCR-ND, BCC oraz BCC-ND. Układ ten pozwala jednocześnie analizować wpływ założenia dotyczącego efektów skali oraz wpływ traktowania części nakładów jako niedecyzyjnych. Wyniki wskazują, że w modelach CRS wpływ nakładów niedecyzyjnych jest niewielki, natomiast w modelach VRS prowadzi do zauważalnych zmian liczby jednostek efektywnych i interpretacji rankingów. Artykuł pokazuje, że DEA może być użytecznym elementem systemu wspomagania decyzji w zarządzaniu kryzysowym, pod warunkiem świadomego doboru specyfikacji modelu i ostrożnej interpretacji wyników.

THE EFFECT OF NON-DISCRETIONARY INPUTS ON CRISIS MANAGEMENT EFFICIENCY ASSESSMENT USING DATA ENVELOPMENT ANALYSIS

Summary. The aim of this article is to assess the impact of incorporating non-discretionary inputs on efficiency measurement results in crisis management. The study is conducted using selected countries' responses to the COVID-19 pandemic during the first 60 days after exceeding the 100-confirmed-case threshold. Four DEA model variants are compared: CCR, CCR-ND, BCC, and BCC-ND. This framework makes it possible to analyse simultaneously the effect of assumptions regarding returns to scale and the effect of treating selected inputs as non-discretionary. The results indicate that, under CRS models, the impact of non-discretionary inputs is limited, whereas under VRS models it leads to noticeable changes in the number of efficient units and in the interpretation of rankings. The article demonstrates that DEA may be a useful component of a decision-support system for crisis management, provided that the model specification is deliberately selected and the results are interpreted with caution.

1. Introduction

The COVID-19 pandemic was one of the most serious global health crises of recent decades. According to the World Health Organisation, as of 2 February 2025 [5],

more than 777.4 million confirmed COVID-19 cases and over 7.0 million deaths had been reported globally. Managing a crisis of this scale required the simultaneous use of multiple policy instruments, including mobility restrictions, social distancing, testing, the organisation of healthcare provision, and, in later phases, vaccination and treatment of infected individuals. The decision-making problem was not limited to the selection of instruments, but also involved their appropriate application under changing epidemiological conditions. Effective crisis management, therefore, requires continuous measurement of the effects of implemented measures and the use of this information as feedback for subsequent decisions.

One method that enables such an assessment is Data Envelopment Analysis (DEA). This method originates from the non-parametric approach to measuring technical efficiency initiated by Farrell [6]. It was further developed in the classical CCR model proposed by Charnes, Cooper and Rhodes [3], and subsequently in the BCC model, which accounts for variable returns to scale, introduced by Banker, Charnes and Cooper [1]. DEA enables the relative efficiency assessment of decision-making units that use multiple inputs to produce multiple outputs, without assigning arbitrary weights to individual variables [4]. In public-sector applications, the classical assumption that all inputs can be freely controlled by the Decision-Making Unit (DMU) is often problematic. During the pandemic, countries operated under different demographic and spatial conditions. Some of these conditions, such as population density, median age, or the share of older people, affected the difficulty of limiting the pandemic's consequences but could not be changed by public authorities in the short term. In the DEA literature, such variables are referred to as non-discretionary inputs or exogenously fixed inputs [2, 7]. In practical terms, non-discretionary inputs are factors that affect a unit's ability to transform resources into outcomes but remain beyond the control of its decision-makers, at least within the time horizon of the analysis. Ignoring them may distort efficiency comparisons, because units operating under unfavourable external conditions can be classified as inefficient even when their managerial decisions were sound.

The aim of this article is to assess the impact of incorporating non-discretionary inputs on efficiency measurement results in crisis management, using responses from selected countries to the COVID-19 pandemic as an example. The study compares four variants of DEA models: CCR, CCR-ND, BCC and BCC-ND. This makes it possible to answer two questions: whether the results change when non-discretionary inputs are incorporated, and whether this effect depends on the adopted assumption regarding returns to scale.

The article is comparative and interpretative in nature. It does not aim to identify a single definitive ranking of countries, but rather to show the extent to which efficiency results depend on the adopted model specification. This approach reduces the risk of treating DEA as a "black box" tool and allows for a clearer distinction between the efficiency of managerial actions and the influence of external conditions.

2. Methodology

The methodology of the study is based on a comparison of four variants of DEA models. The first is the classical CCR model, which assumes constant returns to scale and full discretion over all inputs. The second is the CCR-ND model, which retains the

assumption of constant returns to scale but introduces a distinction between discretionary and non-discretionary inputs. The third model is the classical BCC model, which assumes variable returns to scale. The fourth variant is the BCC-ND model, in which variable returns to scale are combined with non-discretionary inputs. This model structure enables analysis of two sources of differences in the results. First, it enables assessment of the effects of the returns-to-scale assumption by comparing the CCR and BCC models, as well as the CCR-ND and BCC-ND models. Second, it allows the impact of non-discretionary inputs to be determined by comparing the CCR vs CCR-ND and BCC vs BCC-ND pairs. All models are based on the same set of countries, the same observation period, and the same variable structure.

The DMUs are countries analysed for their responses to the COVID-19 pandemic. Each country is treated as a DMU, that is, an entity that transforms specific inputs and operating conditions into outputs related to limiting the consequences of the pandemic. The time scope covers the first 60 days after the threshold of 100 confirmed COVID-19 infection cases was exceeded in a given country. This approach reduces the problem of incomparability resulting from differences in the timing of the pandemic's emergence across countries. The study uses variables describing healthcare system resources, the scale of diagnostic activities, demographic and spatial conditions, and the course of the pandemic. The variables are divided into discretionary inputs, non-discretionary inputs and outputs. Discretionary inputs include healthcare expenditure per capita, the number of tests performed after 60 days per 1,000 inhabitants, and the number of hospital beds per 1,000 inhabitants. Non-discretionary inputs include population density, median age and the share of people aged 65 and over.

The outputs describe the course of the pandemic: the growth rate of cases, the number of cases after 60 days per 1 million inhabitants, the growth rate of deaths, and the number of deaths after 60 days per 1 million inhabitants. Since these variables are undesirable outputs, their reciprocals are used in the DEA models. As a result, lower numbers of infections, lower numbers of deaths, and lower pandemic dynamics translate into higher values of desirable outputs.

The classical CCR model assumes constant returns to scale and full discretion over all inputs. In the input-oriented formulation, the efficiency of a unit is assessed by the extent to which inputs can be proportionally reduced while maintaining at least the existing level of outputs. For the evaluated unit o , the CCR model can be written in envelopment form (1)–(4).

$$\min \theta_o \quad (1)$$

subject to:

$$\sum_{j=1}^J x_{ij} \lambda_j \leq \theta_o x_{io}, \quad i = 1, 2, \dots, I, \quad (2)$$

$$\sum_{j=1}^J y_{rj} \lambda_j \geq y_{ro}, \quad r = 1, 2, \dots, R, \quad (3)$$

$$\lambda_j \geq 0, \quad j = 1, 2, \dots, J \quad (4)$$

where:

- i – index of the i -th input,
- r – index of the r -th output,
- j – index of the j -th unit (DMU),
- λ_j – decision variable: weight assigned to unit j ,
- x_{ij} – discretionary-input vector of unit j ,
- y_{rj} – vector of desirable outputs produced by unit j ,
- θ_o – efficiency score of unit o .

The BCC model differs from the CCR model by adding the convexity constraint (5).

$$\sum_{j=1}^J \lambda_j = 1 \quad (5)$$

This constraint reflects the assumption of variable returns to scale and means that the evaluated unit is assessed against a more local reference technology. As a result, the BCC model usually identifies a larger number of efficient units than the CCR model, because it separates pure technical efficiency due to operating scale [1]. In the CCR-ND and BCC-ND models, the set of inputs is divided into discretionary inputs (D) and non-discretionary inputs (ND). Discretionary inputs are subject to radial reduction, whereas non-discretionary inputs are introduced into the model through separate constraints and are not multiplied by the parameter θ_o . In the model with non-discretionary inputs, the input constraints are (6)-(7).

$$\sum_{j=1}^J x_{ij} \lambda_j \leq \theta_o x_{io}, \quad i = 1, 2, \dots, I, \quad (6)$$

$$\sum_{j=1}^J x_{lj}^{ND} \lambda_j \leq x_{lo}^{ND}, \quad l = 1, 2, \dots, L, \quad (7)$$

where:

- l – index of the l -th non-discretionary input,
- x_{lj}^{ND} – non-discretionary-input vector of unit j .

This formulation means that only discretionary inputs are subject to reduction, whereas demographic and spatial factors serve as constraints limiting the selection of reference units. Consequently, the evaluated DMU is not directly penalised for conditions that it could not change during The analysed period.

3. Results

The results were calculated for 31 countries. In each model, an efficiency score of 1 indicates a unit located on the efficiency frontier, whereas values below 1 indicate relative inefficiency. The descriptive statistics show that the impact of non-discretionary inputs depends on the adopted reference technology. Detailed efficiency scores for all countries are presented in table 1.

Under CRS, the number of efficient DMUs is the same (tab. 2): in both the CCR and CCR-ND models, seven countries achieved full efficiency. The mean efficiency scores are virtually identical: 0.434 in both the CCR and CCR-ND models. Under VRS, the impact of non-discretionary inputs is considerably stronger. In the classical BCC model, 13 countries were efficient, whereas in the BCC-ND model this number increased

Table 1

Efficiency scores in the CCR, CCR-ND, BCC and BCC-ND models

Country	CCR	CCR-ND	BCC	BCC-ND
Belgium	0.038	0.038	0.602	0.638
Czechia	0.240	0.240	0.689	0.740
Denmark	0.168	0.168	0.935	0.935
Germany	0.066	0.066	0.461	0.461
Estonia	0.614	0.614	0.967	1.000
Ireland	0.066	0.066	0.850	1.000
Greece	1.000	1.000	1.000	1.000
Spain	0.060	0.060	1.000	1.000
France	0.092	0.092	0.806	1.000
Italy	0.087	0.087	0.960	0.960
Latvia	1.000	1.000	1.000	1.000
Lithuania	0.574	0.574	0.786	0.814
Luxembourg	0.205	0.205	0.663	0.817
Hungary	0.746	0.746	1.000	1.000
Austria	0.078	0.078	0.501	0.512
Poland	0.475	0.475	1.000	1.000
Portugal	0.092	0.092	1.000	1.000
Slovenia	0.920	0.920	0.963	0.964
Slovakia	1.000	1.000	1.000	1.000
Finland	0.415	0.415	0.873	1.000
Sweden	0.209	0.209	1.000	1.000
Iceland	1.000	1.000	1.000	1.000
Norway	0.213	0.213	0.693	0.829
Switzerland	0.057	0.057	0.560	0.562
United States	0.099	0.099	0.802	1.000
United Kingdom	0.134	0.134	1.000	1.000
South Korea	0.634	0.634	0.876	1.000
New Zealand	1.000	1.000	1.000	1.000
Japan	1.000	1.000	1.000	1.000
Canada	0.172	0.181	0.954	1.000
Australia	1.000	1.000	1.000	1.000

to 20. The mean efficiency score increased from 0.869 to 0.911, and the median in the BCC-ND model reached 1.

In the CCR model, the following countries achieved efficiency: Greece, Latvia, Slovakia, Iceland, New Zealand, Japan and Australia. The same group of countries remained efficient in the CCR-ND model. This means that, under the assumption of constant returns to scale, incorporating non-discretionary inputs did not change the composition of the efficiency frontier. The scores of the remaining countries were also almost identical; a noticeable, although small, change was observed mainly for Canada, whose score increased from 0.172 to 0.181.

Table 2

Basic statistics of DEA model results			
Model	Number of efficient DMUs	Mean	Median
CCR	7	0.434	0.213
CCR-ND	7	0.434	0.213
BCC	13	0.869	0.960
BCC-ND	20	0.911	1.000

The BCC model, which assumes variable returns to scale, identified a larger number of efficient DMUs than the CCR model. Full efficiency was achieved by Greece, Spain, Latvia, Hungary, Poland, Portugal, Slovakia, Sweden, Iceland, the United Kingdom, New Zealand, Japan and Australia. After non-discretionary inputs were incorporated into the BCC-ND model, the number of efficient countries increased to 20. Some of these countries, although below the efficiency frontier in the classical BCC model, achieved full efficiency after demographic and spatial conditions were taken into account – table 3.

Table 3

Largest increases in efficiency after incorporating non-discretionary inputs in the BCC model

Country	BCC	BCC-ND	Difference
United States	0.802	1.000	0.198
France	0.806	1.000	0.194
Luxembourg	0.663	0.817	0.154
Ireland	0.850	1.000	0.150
Norway	0.693	0.829	0.136
Finland	0.873	1.000	0.127
South Korea	0.876	1.000	0.124
Czechia	0.689	0.740	0.050

4. Discussion

The obtained results should be interpreted in relation to the adopted structure of inputs and outputs. The analysed countries differed substantially in discretionary inputs, such as healthcare expenditure, testing intensity, and hospital bed availability, as well as in non-discretionary demographic and spatial conditions. The results show that no single input explains efficiency on its own. Rather, efficiency depends on the overall configuration of resources, external conditions and pandemic outcomes.

The efficient countries identified in the CCR model did not form a homogeneous group. Some achieved efficiency with relatively low healthcare expenditure and favourable pandemic outcomes, while others benefited from low population density, high testing intensity or extensive healthcare infrastructure. This confirms that DEA does not

identify one universal crisis management strategy. The efficiency frontier may be shaped by different combinations of inputs and outputs.

The interpretation of inefficient countries also requires caution. Low efficiency scores do not necessarily indicate a lack of resources, but rather an unfavourable relationship between resources and outcomes. For example, countries with high healthcare expenditure or a large number of hospital beds were not automatically classified as efficient if their pandemic outcomes were weak relative to the best observed configurations in the sample. DEA therefore evaluates relative performance rather than the absolute level of resources.

The key finding is that the impact of non-discretionary inputs depends on the assumed returns to scale. In the CCR and CCR-ND models, the differences were marginal, suggesting that under CRS technology, the inclusion of non-discretionary inputs did not substantially change the set of reference DMUs. In contrast, the comparison between BCC and BCC-ND showed a clear increase in the number of efficient DMUs and more pronounced changes in rankings. This indicates that non-discretionary inputs become particularly important when variable returns to scale are allowed, and more local comparisons between DMUs are permitted.

The BCC-ND model should not, however, be treated as automatically superior to the classical BCC model. Incorporating non-discretionary inputs increases the realism of comparisons but may reduce the model's discriminatory power because more DMUs are classified as efficient. For this reason, the CCR, CCR-ND, BCC and BCC-ND models should be interpreted as complementary tools, each capturing a different aspect of efficiency.

From a crisis management perspective, the results suggest that efficiency assessment should account for both resources controlled by decision-makers and external conditions beyond their short-term control. DEA benchmarks should therefore be treated as reference points rather than direct public policy prescriptions. They may support organisational learning by showing which configurations of inputs and outcomes were associated with efficiency, but they should not be used to produce automatic or definitive rankings of countries.

The study has several limitations. It covers only the first 60 days after each country exceeded the threshold of 100 confirmed cases, and therefore refers to the initial phase of the pandemic. The comparability of infection and death data may also be affected by differences in reporting procedures, testing strategies and death classifications. Moreover, the distinction between discretionary and non-discretionary inputs is partly research-specific. Finally, DEA measures relative efficiency within the analysed sample, not the absolute effectiveness of the pandemic response.

5. Conclusions

The aim of this article was to assess how incorporating non-discretionary inputs affects the measurement of crisis management efficiency. The study compared four DEA models: CCR, CCR-ND, BCC, and BCC-ND, using responses from selected countries to the COVID-19 pandemic as an example.

The results show that the impact of non-discretionary inputs depends on the reference technology adopted. Under CRS, the differences between CCR and CCR-ND

were minimal: the number of efficient DMUs remained unchanged, and the ranking was almost identical. Under VRS, however, the inclusion of non-discretionary inputs led to a clear increase in the number of efficient DMUs and noticeable changes in the scores of some countries. From a methodological perspective, the classical and ND models should be treated as complementary rather than contradictory. CCR and BCC assess efficiency under the assumption that all inputs are fully discretionary, whereas CCR-ND and BCC-ND account for conditions beyond the short-term control of decision-makers. From the perspective of crisis management, the findings confirm that a high level of resources does not automatically translate into high efficiency. DEA may therefore support decision-making and organisational learning, but its results should be interpreted with caution and not treated as definitive country rankings. Further research should extend the analysis to later phases of the pandemic, apply dynamic approaches such as the Malmquist index, and include additional variables related to restrictions, mobility, institutional quality and administrative digitalisation.

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LITERATURE

1. Banker R. D., Charnes A., Cooper W. W.: Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, 1984, Vol.30(9), p. 1078–1092.
2. Banker R. D., Morey R. C.: Efficiency analysis for exogenously fixed inputs and outputs. *Operations Research*, 1986, Vol.34(4), p. 513–521.
3. Charnes A., Cooper W. W., Rhodes E.: Measuring the efficiency of decision making units. *European Journal of Operational Research*, 1978, Vol.2(6), p. 429–444.
4. Cooper W. W., Seiford L. M., Tone K.: *Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software*. Second Edition. Springer 2007.
5. COVID-19 epidemiological update – edition 177, World Health Organization. <https://www.who.int/publications/m/item/covid-19-epidemiological-update-edition-177> 2025. Accessed on 26 June 2026.
6. Farrell M. J.: The measurement of productive efficiency. *Journal of the Royal Statistical Society. Series A (General)*, 1957, Vol.120(3), p. 253–281.
7. Ruggiero J.: Performance evaluation when non-discretionary factors correlate with technical efficiency. *European Journal of Operational Research*, 2004, Vol.159(1), p. 250–257.