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Interfaces with Other Disciplines

Determining sources of relative inefficiency in heterogeneous samples: Methodology using Cluster Analysis, DEA and Neural Networks

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ABSTRACT

Data Envelopment Analysis (DEA) is a powerful data analytic tool that is widely used by researchers and practitioners alike to assess relative performance of Decision Making Units (DMU). Commonly, the difference in the scores of relative performance of DMUs in the sample is considered to reflect their differences in the efficiency of conversion of inputs into outputs. In the presence of scale heterogeneity, however, the source of the difference in scores becomes less clear, for it is also possible that the difference in scores is caused by heterogeneity of the levels of inputs and outputs of DMUs in the sample. By augmenting DEA with Cluster Analysis (CA) and Neural Networks (NN), we propose a five-step methodology allowing an investigator to determine whether the difference in the scores of scale heterogeneous DMUs is due to the heterogeneity of the levels of inputs and outputs, or whether it is caused by their efficiency of conversion of inputs into outputs. An illustrative example demonstrates the application of the proposed methodology in action.

1. Introduction

Data Envelopment Analysis (DEA) is a widely used non-parametric analytic tool (e.g. Amado and Dyson, 2008; Camanho and Dyson, 2005; Sarrico and Dyson, 2004; Chen and van Dalen, 2010; Khalili et al., 2010; Asmild et al., 2007; Shao and Lin, 2001; Gillen and Lall, 1997; Khouja, 1995; Doyle and Green, 1994) that is commonly applied in the research and practitioner communities to determine the relative efficiencies of the *Decision Making Units* (DMU). Any entity that receives a set of inputs and produces a set of outputs could be designated as a DMU, thus, any group of such entities could be subjected to DEA. As a result, this method has been applied to evaluate productivity and performance of airports (Gillen and Lall, 1997; Martin and Roman, 2001; Pels et al., 2001), efficiency of US Air Force maintenance units (Charnes et al., 1985), hospitals (Grosskopf et al., 2001; Gruca and Nath, 2001; Kirigia et al., 2001; Sola and Prior, 2001), university departments (Beasley, 1990), schools (Bessent and Bessent, 1980; Santos and Themido, 2001; Portela and Thanassoulis, 2001; Grosskopf and Moutray, 2001), counties (Raab and Lichty, 1997), as well as to compare industries and sectors (Sueyoshi and Goto, 2001; Navarro and Camacho, 2001; Murillo-Zamorano and Vega-Cervera, 2001; Mathijs and Swinnen, 2001), banks (Mukherjee et al., 2001; Sathye, 2001; Kuosmanen and Post, 2001; Hartman et al., 2001; Lin et al., 2009; Schaffnit et al., 1997), products and services (Doyle and Green, 1991; Hollingsworth and Parkin, 2001; Johnston and Gerard, 2001), computers (Doyle and Green, 1994), regulations (Piot-Lepetit et al., 2001; Gronli, 2001), strategic decision making (Demirbag et al., 2010), and technologies (Khouja, 1995; Shao and Lin, 2001; Ramanathan, 2001; Pare and Sicotte, 2001).

One of the fundamental assumptions of DEA is that all DMUs in the sample are *functionally similar* in the sense that all DMUs receive the same *number* and the same *type* of inputs and outputs. The compliance with this assumption is enforced by defining a common *DEA model*, according to which the evaluation of the relative efficiency of every DMU in the sample takes place. DEA treats a DMU as a collection of inputs and outputs, without any regard to the actual process by which conversion of inputs into outputs takes place; instead, the process of conversion is treated by DEA as a "black box" common to all DMUs in the sample. Another fundamental assumption of DEA is that a set of DMUs is *homogenous* in the sense that all DMUs are "alike" and thus directly comparable. Compliance with this important assumption of *homogeneity* of the sample is not enforced in DEA and usually resides under implicit purview of the decision maker. We suggest that two factors are important for the assumption of homogeneity of DMUs to hold. The first factor, *semantic homogeneity*, refers to the common meaning that is assigned to all DMUs in the sample by the decision maker. Compliance with this factor is straightforward. The second factor, *scale homogeneity*, refers to the *levels* of inputs and outputs

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of each DMU in the sample. In the absence of perfect scalability, the compliance with the second factor is problematic, for the decision maker must ensure that the levels of inputs and outputs are not affecting the functional similarity of DMUs in the sample.

However, in many situations the sample of DMUs is a sample of convenience. It is possible, under such circumstances, that an investigator conducts DEA using a sample consisting of DMUs that are functionally similar, semantically homogeneous, yet heterogeneous in terms of the levels of inputs and outputs, which would mean that the validity of the resulting relative efficiency scores would be questionable since the *homogeneity* assumption holds only partially.

We must note that we are not drawing attention of the reader to the obvious case where scale heterogeneity arises simply due to the differences in the scale of the transformation of inputs into outputs, with all other factors being constant. The scale heterogeneity could be easily countered through the use of a scaling factor. Instead, we are interested in the cases where scale heterogeneity arises because of a more complex, not clearly obvious, scaling pattern that makes creation of any accurate sub categorization problematic. Let us consider an example of a comparison of a group of hospitals ranging in size from small to large. Clearly, the significant differences in the levels of inputs and outputs of such hospitals, whatever they might be, are important in themselves. However, it is also possible that such heterogeneity of the levels of inputs and outputs is reflective of the differences among the other important dimensions that are not accounted for by DEA model. In many cases a large hospital is a very different enterprise, from a standpoint of quality, complexity and technological sophistication, than a small hospital.

Let us take this example further and consider that a smaller hospital A turned out to be relatively less efficient than a larger hospital B. Based on the results of the DEA of such *scale heterogeneous* sample of hospitals, the decision maker interested in improving efficiency of hospital A would face two possible options. The first option is to reduce the level of relative inefficiency of hospital A by improving the efficiency of the process by which inputs are converted into outputs. However, one cannot rule out that a lower level of relative efficiency of a hospital A is due to the comparatively lower level of inputs that it receives. Consequently, the second option is to reduce the level of relative inefficiency of hospital A by affecting the level of *scale heterogeneity*, i.e., to change the existing level of inputs. The question becomes, then, what option is to be pursued? Considering this, in our study we aim to investigate the following research question:

How to account for the differences in the relative efficiency scores of the DMUs in the sample in the presence of scale heterogeneity associated with a complex and non-obvious scaling pattern?

Our inquiry relies on the assumption that the difference in the relative efficiencies of the DMUs in a *scale heterogeneous* sample could arise from the two sources. The first source reflects the difference in the *transformative capacity* of the DMUs, which reflects the "true" difference in the relative efficiencies of the DMUs in terms of the conversion of the set of inputs into the set of outputs. The second source reflects *scale heterogeneity* of the DMUs in the sample and is indicative of the difference in the *levels* of inputs and outputs associated with a complex and non-obvious scaling pattern.

We suggest that the assumption of homogeneity of a sample of DMUs should not be taken for granted, but explicitly tested for. The reader may note that this position is similar to what applies in statistical analysis where there is explicit testing of the normality assumption. Consequently, in the situation where an investigator needs to perform DEA, we suggest a multi-step methodology that is an extension of our previous work aimed at the increasing the discriminatory power of DEA (Samoilenko and Osei-Bryson, 2008). In order to present our methodology, we structure this paper as follows. In Section 2, we briefly overview some common approaches of combining DEA with Cluster Analysis and Neural Networks. Section 3 offers an overview of the component techniques utilized in our methodology. Section 4 provides an application of the methodology on an illustrative dataset. A Brief conclusion is presented in Section 5.

2. DEA with Cluster Analysis and Neural Networks

2.1. Cluster Analysis (CA) and DEA

Clustering is a popular data mining technique (e.g. Rai et al., 2005; Okazaki, 2006; Wallace et al., 2004; Cristofor and Simovici, 2002; Dhillon, 2001; Ben-Dor and Yakhini, 1999; Huang, 1997; Fisher, 1997; Banfield and Raftery, 1992) that involves the partitioning of a set of objects into a useful set of mutually exclusive clusters such that the similarity between the observations within each cluster (i.e. subset) is high, while the similarity between the observations from the different clusters is low.

The approach of using CA with DEA is not novel to this research (Shin and Sohn, 2004; Hirschberg and Lye, 2001; Lemos et al., 2005; Meimand et al., 2002; Sharma and Yu, 2009; Marroquin et al., 2008; Schreyögg and von Reitzenstein, 2008). In general, CA could be incorporated with DEA in two distinct ways. The first approach is to apply CA to the results of DEA with the purpose of constructing multiple reference subsets from the original set of DMUs (Meimand et al., 2002; Bojnec and Latruffe, 2007). Another approach calls for limiting a comparison of each DMU to its reference subset. As a result of this approach the efficiency score of a DMU is defined not by an efficient subset of all DMUs, also called a *peer group*, but only by an efficient subset of its *peer subgroup*. Consequently, in the presence of scale heterogeneity of the sample this approach will results in isolation of the multiple homogeneous subsets (Azadeh et al., 2007), and then in comparing each DMU only with the appropriate subset consisting of its peers within the subset. While the use of this method offers obvious benefits, the shortcoming of this approach is that the relative efficiency of a DMU could only be determined in reference to its subset peer group, rather than to the sample as a whole.

Similar to the mentioned above approaches, our study proposes a solution to conducting DEA of a scale heterogeneous data set by means of using CA. Unlike the other approaches, our method does not require explicit partitioning of the sample of DMUs into multiple peer groups, nor does it require a large data set, neither does it require any external to DEA data, such as "external comparators" mentioned by Dyson et al. (2001) and used by Sarrico and Dyson (2000). Instead, our method aims at identifying and taking into consideration the presence of heterogeneous subsets without actually dividing the sample. As a result, our approach is not incongruent with one suggested in Dyson et al. (2001), where grouping of DMUs into homogenous subsets is based on management information; furthermore, we suggest that our method could aid the decision maker's judgment by increasing available to her additional information in the form of the results of CA. Consequently, similarly to the approach of Athanassopoulos and Thanassoulis (1995), our method results not in physical, but rather in *logical partitioning* of the otherwise intact data set that is subjected to DEA.

2.2. Neural Networks (NN) and DEA

Neural Network (NN) modeling aims to develop a "black box" model (i.e. an Artificial Neural Network) of the unknown complex relationships in the data. This data mining method is particularly appropriate when there is no known mathematical formula that relates the input and output variables, and prediction is more important than explanation. It has been used extensively by researchers (Pao and Sobajic, 1991; Vai and Xu, 1995; Lu et al., 1996; Crestani and van Rijsbergen, 1997; Choi and Yoo, 2001; Bu et al., 2003; Harb and Chen, 2005).

Using NN in conjunction with DEA is also not novel to this investigation. Combination of DEA and NN in one study started with the work of Athanassopoulos and Curram (1996), who extended the comparison of DEA with corrected ordinary least squares methods (Banker et al., 1993) to the comparison of DEA with NN. For the purposes of estimating efficiency frontiers, NN could be perceived as a possible alternative (Costa and Markellos, 1997; Santin and Valino, 2000; Wang, 2003; Santin et al., 2004; Azadeh et al., 2007), or as a complement to DEA (Pendharkar and Rodger, 2003; Angelidis and Lyroudi, 2006; Wu et al., 2006; Celebi and Bayraktar, 2008; Emrouznejad and Shale, 2009; Mostafa, 2009; Wu, 2009).

We believe that NN can augment, rather than replace DEA, and in our methodology we employ NN as a complementary to DEA technique. What differentiates our approach, however, is that we use NN for the purposes of simulating the values of outputs of DEA model based on which scores of the relative efficiency of DMUs will be calculated, and not for the purposes of classifying DMUs in terms of the relative efficiency (e.g., Wu, 2009), or predicting the scores of relative efficiency of DMUs (e.g., Emrouznejad and Shale, 2009), or pre-processing of the data prior to DEA (Celebi and Bayraktar, 2008).

The fact that DEA and NN lack the explanatory power to provide insights regarding the *mechanism of transformation* does not negate the capability of these methods to provide inquirers with the insights regarding the *results of transformation*. The "black box" approach used by both methods fits the purpose of our study well, for we are not trying to determine *how* scale heterogeneity affects relative efficiency of DMU; instead, we are interested in the *presence* of the effect. This brief overview of such complex subject as NN cannot do justice to the topic. Thus, we direct the interested reader to Bishop (1995) for a comprehensive treatment of the subject.

3. Description of the methodology

The proposed methodology helps an investigator to address two potential problems that arise when conducting DEA. First problem is associated with a possible non-homogenous environment of DMUs (Dyson et al., 2001), which, due to its complexity, cannot be dealt with by simple inclusion of environmental variables in DEA model. For example, if we are to compare two hospitals in different states in the USA, in order to account for a possible heterogeneity of their environment we would need to include some sort of environmental variables reflecting the differences in social, political, environmental, legal, and cultural environments. Dyson et al. (2001) acknowledge that such environmental variables, especially in the service sector, could be difficult to identify, define, and measure. Furthermore, even if it is possible to completely account for the differences in the environment of DMUs and include the environmental variables into DEA model, this approach will result in a possibly significant increase in the number of inputs and output. This, in turn, would lead to the lower level of discrimination (Dyson et al., 2001). And while the authors suggested that this problem can be dealt with by increasing the number of DMUs in the sample, such increase could bring an additional source of non-homogeneity in the sample, which would have to be dealt with by inclusion of new types of environmental variables with all the consequences. The proposed use of NN in our methodology, on the other hand, allows an investigator to capture the impact of the specific environment for each logical subgroup without actually including any environmental variables in DEA model.

The second problem is associated with the available return to scale assumptions of DEA. Let us revisit our earlier example and compare two hospitals in terms of their relative efficiency of the production of revenues from the sale of a new type of service – a novel plastic surgery. The Product Life Cycle (PLC) model informs us that such *sales* curve is S-shaped (Sultan et al., 1990; Mahajan et al., 1995; Rogers, 2003; Van den Bulte and Stremersch, 2004; Hauser et al., 2006). It is commonly accepted that the models that produce S-shaped curves (e.g., logistic curve model or Gompertz model) contain areas of increasing, constant, and decreasing return to scale. Using DEA to compare relative efficiency of two hospitals in such situation will require an investigator to impose two additional assumptions. First, it will be required to assume that our two hospitals are in the same phase of the *sales* curve (e.g., introduction, growth, maturity, or decline). Second, it will be required to assume that the estimate of the relative efficiency provided by DEA holds for the duration of the *sales* curve. Our approach utilizes NN to simulate the position of a DMU in more than one point on the *sales* curve, thus, the first assumption can be relaxed. Furthermore, by performing DEA of the simulated data we can obtain multiple scores of the relative efficiency for each DMU, which will allow us to relax the second assumption. Furthermore, using NN simulation in our methodology allows for avoiding DEA-related problems associated with the possible presence of economies and diseconomies of scale; consequently, we suggest adopting the basic CRS model.

The proposed methodology consists of five major steps that are summarized in Table 1; the description of each step follows. As previously mentioned above, the proposed methodology is an extension of the three-step methodology of Samoilenko and Osei-Bryson (2008), which utilizes the CA and DEA as, correspondingly, the first and second steps. Consequently, in this section we provide only a brief description of the first two steps and focus our discussion on the remaining steps of the methodology proposed in this paper.

3.1. Description of Steps 3–5 of the methodology

3.1.1. Step 3: generate a "black box" model of transformative capacity of each cluster

3.1.1.1. Description. For each cluster k, NN induction is used to generate a "black box" model of the transformative capacity of DMUs in the given cluster. Let the model for cluster "k" be labeled BBTM_k. This involves using the set of input variables for each cluster as input nodes, and the set of output variables as output nodes of the NN. Then we train the NN in order to obtain the specific a *non-explanatory"black box" model of the transformative capacity* by which the set of inputs is converted into the set of outputs; we call this *transformation model* of a given cluster.

3.1.2. Step 4: generate simulated sets of the outputs for each cluster

For each cluster k_1, apply the black box transformative model BBTM_{k1} to every other cluster k_2. The result is that for such that for each $\text{DMU}_{i(k2)}$ in a given cluster k_2, simulated outputs are generated based on the application of BBTM_{k1} to the inputs of $\text{DMU}_{i(k2)}$.

3.1.3. Step 5: determine the sources of the relative inefficiency of the DMUs in the sample

For each pair of clusters (k_1, k_2):

(a) Apply DEA to the original inputs of DMUs of cluster k_2 and the corresponding simulated outputs that resulted from BBTM_{k1}.

Table 1
Proposed methodology.

Step	Step 1	Step 2	Step 3	Step4	Step 5
Purpose	Evaluate the Scale Heterogeneity Status of the Dataset	Determine the Relative Efficiency Status of each DMU	Generate a model of Transformative Capacity of each Cluster	Obtain simulated sets of the outputs for each DMU in each cluster	Determine sources of the Relative Efficiencies of the DMUs in the sample
Dataset	Complete Sample	Complete Sample	Clusters generated in Step 1	Clusters generated in Step 1	Complete Sample
Technique	Cluster Analysis (CA)	DEA	Neural Networks (NN)	Neural Networks (NN)	DEA
Outcome	One or more clusters	Scores of averaged relative efficiency for each cluster	"Black box" model of transformative capacity for each cluster	Simulated outputs for each cluster based on "black box" models of other clusters	Scores of averaged relative efficiency for each cluster based on the original inputs and simulated outputs

(b) Calculate the average relative efficiency of cluster k_2 based on the its original inputs & simulated outputs.
(c) Compare this simulated average relative efficiency of cluster k_2 to that of its actual average relative efficiency in order to determine if there is any difference in the transformative capacities of clusters k_1 and k_2.
(d) Compare this simulated average relative efficiency of cluster k_2 to the actual average relative efficiency of cluster k_1 in order to determine if any difference in the average performances of clusters k_1 and k_2 is due, in part, to scale heterogeneity.

3.2. Motivation for Steps 3 and 5 of the Methodology

3.2.1. Motivation for Step 3

The third step of out methodology utilizes NN to create a model of the transformative capacity for each of the *k* clusters identified in Step 1. We propose that modeling of DEA scores can be used for the purposes of inquiring into the factors affecting relative efficiency, albeit indirectly. Despite the fact that the modeling of DEA scores is an often encountered approach (Hoff, 2006), it comes with the penalty of inevitable misspecification of the model according to which inputs are converted into outputs. It is reasonable to suggest, that the correct "white box" modeling of the DEA scores must have at least two prerequisites. First, the investigator must know the model of transformation of inputs into outputs utilized by DEA. Second, it must be possible to re-specify correctly this known model within the data analytic technique that is going to be used for the purposes of modeling of DEA scores. The non-parametric nature of DEA is another point to consider; for use of parametric techniques, such as commonly used for this purpose Tobit regression, not only results in misspecification (Hoff, 2006), but also requires a compliance with the data normality assumption that often used in DEA sample of convenience may not satisfy.

As a result, a misspecification of the model is inevitable; for the "black box" approach of DEA to the process of transformation of inputs into outputs leaves investigator no chance of knowing, let alone specifying, the correct model. Keeping the mentioned above difficulties in mind, we decided instead to model a *new data set*, and then use DEA to obtain a new set of scores. The "black box" approach of NN to modeling complex unknown relationship in the data set fits well for this purpose, for we do not need to know and specify the relationship between the data ourselves.

We use the set of input variables for each cluster as input nodes, and the set of output variables as output nodes of the NN. Then we train the NN and obtain the specific to each cluster *transfer function* according to which the set of inputs is converted into the set of outputs; we call this *transfer function* a *non-explanatory* "*black box*" *model of the transformative capacity* of a given cluster. Consequently, in the Step 3 we end up generating *k* "*black box*" *models* corresponding to each of the *k* clusters identified in Step 1.

When the "black box" models of the transformative capacity generated for every subset of the sample, we have successfully isolated the first factor influencing the relative efficiency of each DMU in the sample, namely, the efficiency of the transformation of the set of inputs into the set of outputs.

3.2.2. Motivation for Step 5

The purposes of this step are: to determine if the DMUs in a given cluster k_2 would have improved performance if they had utilize the transformative model of another cluster k_1; and (2) To determine if any difference is die to scale heterogeneity. For a given cluster this exploration is conducted using the transformative capacity model BBTM_{k1} of every other cluster k_1 where $k_1 \neq k_2$.

Thus if Step 1 had resulted in 2 clusters, *Followers* and *Leaders*, during step 5 we would subject the original inputs and simulated outputs of the *Followers* that were generated in the4, as well as the original inputs and the simulated outputs of the *Leaders*, to DEA. Then we again calculate the averaged scores of the relative efficiency for every cluster and determine whether the averages of the *Followers* have improved. If this is the case, and the average relative efficiencies of the *Followers* have gone up, we have a reason to suggest that the disparity between the relative efficiencies of the *Leaders* and the *Followers* is due, in part, to the differences in their transformative capacities.

At this point, we need to determine a role of*scale heterogeneity* in the disparity of the levels of the relative efficiencies of the *Leaders* and the *Followers*. In order to do so we conduct DEA again, this time using the data set consisting of the original inputs and the outputs of the *Followers*, and the original inputs and simulated outputs of the *Leaders*. Once the scores of the relative efficiency have been obtained, we group them according to the cluster membership (i.e., *Followers* and *Leaders*), and average the relative efficiency scores for each group. If, after the comparison of the averaged relative efficiencies the *Leaders* still have a higher averaged relative efficiency score, then we have a reason to suggest that the disparity between the relative efficiencies of the *Leaders* and the *Followers* is due, in part, to scale heterogeneity. Meaning, even with the less efficient process of the transformative capacity, the *Leaders* are still capable of being more relatively efficient than the *Followers* are.

4. Illustrative example

4.1. Description of the illustrative dataset

We test the proposed methodology in the context of the set of countries classified by IMF (2000) as *Transition economies in Europe and the former Soviet Union.* Using archival data drawn from the *Database of World Development Indicators*, which is the World Bank's comprehensive database on development data, and the *Yearbook of Statistics*, published yearly by International Telecommunication Union (ITU), we aggregated the data on 18 economies for the period from 1993 to 2002. These 18 countries are Albania, Armenia, Azerbaijan, Belarus, Bulgaria, Czech Republic, Estonia, Hungary, Kazakhstan, Kyrgyz Republic, Latvia, Lithuania, Moldova, Poland, Romania, Slovak Republic, Slovenia, and Ukraine. As a result, we constructed the sample consisting of 180 data points, where each data point reflected a given TE per given year. While these economies do share a common classification, they also display some important differences in terms of their levels of economic development, state of infrastructure, business environment, etc. The research on the subject of the effect of investments in Information and Communication Technologies (ICT), such as Telecoms, on economic development in the context of TEs suggested that small number of countries (e.g., Poland, Hungary, Slovenia, and Czech Republic) were able to benefit from investments in ICT. The much larger number of TEs, however, falls short of demonstrating the positive impact of such investments on their economic development. Multiple research studies identified the level of investments in ICT (Murakami, 1997; Piatkowski, 2002) is one of the variables that impact the level of returns on investments.

Consequently, while keeping all the possible differences between 18 TEs in our sample in mind, it is reasonable to suggest that two factors could be responsible for the discrepancy of the effects of the investments in Telecoms on the level of returns on investment. The first factor is a level of investments in Telecoms and the second factor is a level of the efficiency of the transformation of investments in Telecoms into revenues.

To demonstrate our methodology in action, we formulate the following broad research problem:

> *How to determine the appropriate, empirically justifiable route by which TEs could improve their level of relative efficiency of the production of revenues from investments in Telecoms?*

In the context of the illustrative example and our methodology, the answer to this research problem involves answering the following questions:

1. Whether the 18 TEs display significant differences in terms of the levels of investments in Telecoms and revenues from Telecoms (Step 1);
2. Whether the subsets of the sample, which differ in terms of the levels of investments and revenues, also differ in terms of the relative efficiency of the production of revenues (Step 2);
3. Whether the subsets of the sample differ in terms of the processes of transformation on investments into revenues (Steps 3 and 4);
4. Whether the relative inefficiency of poor performers is associated with the insufficient levels of investments or whether it is a result of inefficient processes of the transformation of investments into revenues (Step 5).

4.2. Application of the methodology on the illustrative dataset

For the DEA part of the methodology, we have identified a model consisting of six input and four output variables, presented in Table 2. A theoretical justification of the chosen model and the discussion regarding the choice of the variables can be found in Samoilenko (2008) and Samoilenko and Osei-Bryson (2008).

4.2.1. Results of Step 1: evaluate the scale heterogeneity status of the dataset

To perform CA we employed a partitional approach to generate the maximum possible number of clusters (i.e. k_{Max}), followed by the application of an agglomerative clustering method to combine pairs of clusters until the specified minimum number of clusters (i.e. k_{Min}) is obtained. Given our interest in determining whether a set of DMUs (i.e., 18 TEs) is a *scale heterogeneous*, we will use a user-specified threshold on outlier size to assess whether a given partition contains outlier clusters, and also use expert knowledge to further assess whether the partition is meaningful. A cluster will be considered an outlier if the percentage of the objects that it includes is less than $\tau_{Outlier}$ of the objects in the entire dataset. We are not claiming that this is the only or always best approach, particularly since for a given dataset it is never clear which approach is the most appropriate. Benefit of our approach, however, is that it allows for augmenting a context-independent solution with the context-dependent knowledge of a domain expert.

Table 2
Variables selected for the DEA model.

Input variables of the DEA model	Output variables of the DEA model
GDP per capita (in current US $)	Total telecom services revenue per telecom worker
Full-time telecommunication staff (% of total labor force)	
Annual telecom investment per telecom worker	Total telecom services revenue (% of GDP in current US $)
Annual telecom investment (% of GDP in current US $)	
Annual telecom investment per capita	Total telecom services revenue per worker
Annual telecom investment per worker	Total telecom services revenue per capita

We used SAS Enterprise Miner (EM) to perform CA of the data set and we were able to come up with a solution that partitions our data set into two clusters (see Table 3). Based on the compiled information we can see, that while some of the TEs are 'permanent residents' of one cluster, other TEs are 'migrants', i.e., they change the cluster membership depending on a year. Additional details of the results of CA are provided in Appendix of the paper.

4.2.2. Results of Step 2: determine the relative efficiency status of each DMU

To perform DEA we have chosen an output-oriented model and used it under the conditions of constant return to scale (CRS), variable returns to scale (VRS) and non-increasing returns to scale (NIRS). Unlike in the case of the input-oriented model, the output-orientation does not concern itself with the efficient utilization of the inputs, but rather with the maximization of the outputs. Thus, it is probably reflective of the perspective of the investor, especially in the case when the primary goal is to obtain the maximum revenue.

We present the summarized results in Table 4. This approach of using average countries inefficiencies over the period of time, as well as averaged inefficiencies for a group of countries, is consistent with the approach of Arcelus and Arocena (2005). It turned out that the averaged relative efficiency of the second cluster is greater than of the first cluster; consequently, we labeled the first cluster as *Followers* and the second cluster as the *Leaders*.

Table 3
Membership of the 2-cluster solution.

The followers	The leaders
Albania (1993–2002)	Bulgaria (2002)
Armenia (1993–2002)	**Czech Rep (1993–2002)**
Azerbaijan (1993–2002)	Estonia (1994–2002)
Belarus (1993–2002)	**Hungary (1993–2002)**
Bulgaria (1993–2001)	Latvia (1994, 1995, 1997–2002)
Estonia (1993)	Lithuania (1999–2002)
Kazakhstan (1993–2002)	**Poland (1993–2002)**
Kyrgyzstan (1993–2002)	**Slovenia (1993–2002)**
Latvia (1993 and 1996)	Slovakia (1995–1998, 2000–2002)
Lithuania (1993–1998)	
Moldova (1993–2002)	
Romania (1993–2002)	
Slovakia (1993, 1994, 1999)	
Ukraine (1993–2002)	

Table 4
DEA: Comparison of the clusters based on the output-oriented DEA model.

Relative efficiency score	Leaders	Followers	Difference	Difference %
CRS, average	**1.94**	**2.54**	−**0.60**	**23.67**%

4.2.3. Results of Steps 3 and 4: generate simulated sets of the outputs for each cluster based on black box models transformative capacity processes

To conduct NN simulation of the outputs of our DEA model we used *Enterprise Miner* (a part of SAS 9.1 package by SAS Institute). For the purposes of this research, we used supervised mode of learning because the data set that we are going to use contains not only the inputs, but also the outputs. First, we used NN to simulate the outputs of the *Followers* based on the transformative capacity of the *Leaders*. We used the setting allowing us to use "Samples of data sets" for preliminary training. We also used "Average Error" as our model selection criterion; this setting chooses the model with the smallest average error for the validation data set. Other settings were: "none" as the number of preliminary runs and "standard back propagation" as a training technique. After the running of the model the convergence criterion was satisfied.

The process model diagram depicting stages involved into the simulation of the outputs is represented in Fig. 1. Once the simulated outputs of the Followers were obtained, we used the same process to obtain the simulated outputs of the *Leaders* based on the transformative capacity of the *Followers*.

4.2.4. Results of Step 5

Once the simulated outputs were obtained, they were substituted instead of the real outputs. After that, we have conducted the DEA again and obtained the new values of relative efficiencies for the *Followers* and the *Leaders*. We adapted the approach used by Arcelus and Arocena (2000) and used averaged values of relative efficiency scores. The results are summarized in Table 5.

Based on the results of the DEA we are able to establish that the *Followers* are capable of becoming more efficient than the *Leaders* in the case if they improve the level of the transformative capacity. Thus, at this point we can state that the lower level of the averaged relative efficiency of the *Followers* is, at least partially, a result of the inefficient processes of the revenue production. The results summarized in Table 5 also indicate, that the increase in the level of the inputs does not improve the level of relative efficiency of the *Followers*. Consequently, prior to increasing the level of the investments in Telecoms, the *Followers* must improve the effectiveness of the revenue production associated with the current level of the investments.

5. Discussion and conclusion

The non-parametric nature of DEA does not present a problem for the assessment of relative efficiency of technological artifacts, as long as they belong to the same domain.

When we attempt to compare level of performance of natural, social, or socio-technical entities we immediately end up on a fundamentally unstable ground, for there is very little we can do to ensure that subjects of our comparison are "alike". Let us consider some purely hypothetical examples. First, we compare a performance of two basketball players, Star and NotStar, in terms of their efficiency of converting minutes on the court into the points. Star, whose relative efficiency is higher, averages 35 minutes and 30 points per game, while NotStar, whose relative efficiency is lower, averages 5 minutes and three points per game. There are two possible explanations regarding the difference in the level of performance: first, Star is a better player than NotStar, second, Star is spending more time on the court. Now, how do we go about increasing relative efficiency of NotStar? Do we proceed by allowing him to play more minutes, or by trying to make him a better player first?

Similarly, how do investors should go about increasing the level of performance of the less successful baseball teams in Major League Baseball? Should investors provide incentives for a better performance, or should they start from investing more in the team's roster, hoping that the results will follow? Essentially, this is a type of a problem that our methodology allows us to address.

Let us consider an example of possible application of the proposed methodology, which is closer in spirit and relevance to the illustrative example that we used in this paper. On November 20, 2001, the UN Secretary-General established, per request from the United Nations Economic and Social Council, an Information and Communication Technologies Task Force (ICTF). The purpose of this initiative was to provide a global dimension to the efforts in bridging of the 'digital divide', to encourage digital opportunity, and to place information and communication technologies (ICT) at the service of the development for all countries (Martinez-Frias, 2003). At this point, we know that in terms of the bridging digital divide the level of success from the investments in ICT varies greatly from country to country. However, we do not know whether the variation in the results is due to differences in the levels of the investments of ICT, or whether it is due to the capability of a given economy to transform the investments into the outcomes, i.e., bridging the digital divide. The answer to this question is very important, for it serves as one of the determinants of the investment strategy directed at the accomplishment of the goals of ICTF. We hope that we were able to demonstrate the possible contribution of the proposed methodology from practical standpoint.

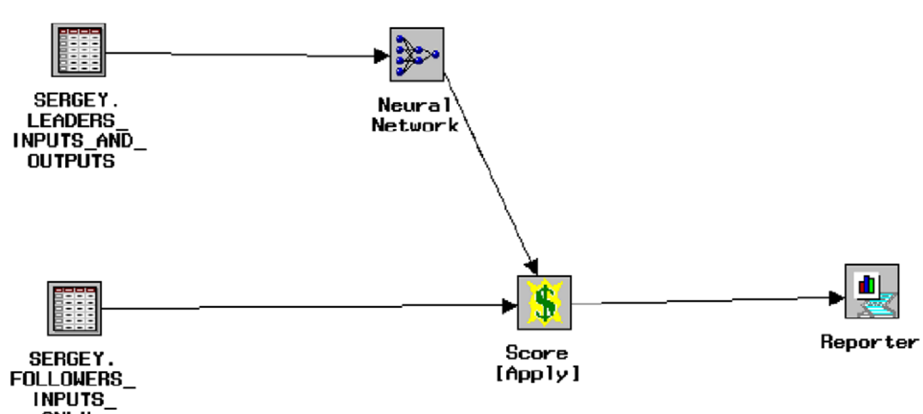


Fig. 1. The process model diagram of NN simulation.

Table 5
Summary of Step 5.

Comparison of the DEA scores based on	Leaders, CRS Averaged (Actual)	Followers, CRS Averaged (Simulated)	Difference	Difference %
The simulated data of the *followers* and the actual of the *Leaders*	**2.04**	**1.62**	**0.42**	**25.62%**
The simulated data of the *leaders* and the actual of the *Followers*	**2.09**	**2.30**	**−0.21**	**9.20%**

We suggest that the proposed approach makes methodological contributions as well. First, our methodology allows for increasing the discriminatory power of DEA in the samples with the presence of heterogeneity. While traditional DEA alone categorizes DMUs in the sample as being relatively efficient or relatively inefficient, our approach allows for placing each DMU in one of the three categories. These categories are first, relatively efficient, second, relatively inefficient due to scale heterogeneity of the sample, and third, relatively inefficient due to transformative capacity. Second, our methodology allows for explicit acknowledging of the heterogeneity of the sample of DMUs, thus greatly expanding the domain of eligible for DEA DMUs. Finally, our approach allows for increasing prescriptive capabilities of DEA, providing a decision maker with distinct strategies regarding the increase of relative performance for each DMU in a non-homogenous sample.

We must acknowledge, however, that our research is not without its limitations. First, despite applying CA to evaluate a sample of DMUs for heterogeneity, our approach does not provide any strict criteria regarding to what constitutes heterogeneity of the sample. Consequently, because heterogeneity is a relative concept, and because the determination of heterogeneity often requires intimate knowledge of the problem domain, we declare this issue as being beyond the scope of our methodology and delegate it to reside under the purview of an investigator.

Second limitation of our study is associated with the assumption regarding the sources of relative inefficiency in the non-homogenous sample. We assume that heterogeneity of the sample *or* a transformative capacity of DMUs can cause relative inefficiency. However, it is possible that there is interplay between the two factors, where heterogeneity of the sample affects transformative capacity or, conversely, heterogeneity arises due to the differences in transformative capacity. Nevertheless, we hope that contributions of our study outweigh its limitations.

Appendix A. Results of cluster analysis

Distance between two clusters

CLUSTER	Cluster 1	Cluster 2
1	0	1232316620
2	1232316620.9	

Appendix B. Results of cluster analysis

Variables used in partitioning of the data set

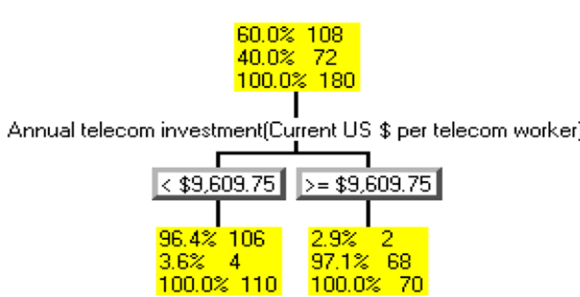
Name	Importance	Measurement	Type	Label
TOTAL_TELECOM_SERVICES_REVENUE_C	0	interval	num	Total telecom services revenue(Current US $)
TOTAL_TELECOM_SERVICES_REVENUE_0	0	interval	num	Total telecom services revenue(Current US $ per perso
TOTAL_TELECOM_SERVICES_REVENUE_1	0	interval	num	Total telecom services revenue(Current US $ per worke
ANNUAL_TELECOM_INVESTMENT_CURREN	0	interval	num	Annual telecom investment(Current US $)
ANNUAL_TELECOM_INVESTMENT_CURRE0	0	interval	num	Annual telecom investment(Current US $ per person)
ANNUAL_TELECOM_INVESTMENT____OF_	0	interval	num	Annual telecom investment(% of GDP)
ANNUAL_TELECOM_INVESTMENT_CURRE1	0	interval	num	Annual telecom investment(Current US $ per worker)
ANNUAL_TELECOM_INVESTMENT_CURRE2	1	interval	num	Annual telecom investment(Current US $ per telecom wo
TOTAL_TELECOM_SERVICES_REVENUE_2	0	interval	num	Total telecom services revenue(Current US $ per tele
PRODUCTIVITY_RATIO_PER_TELECOM_W	0	interval	num	Productivity ratio per telecom worker (revenue/invest
FULL_TIME_TELECOMMUNICATION_STAF	0	interval	num	Full-time telecommunication staff(% of total labor fo

Appendix C. Results of cluster analysis

Cluster's membership

CLUSTER	Frequency of Cluster	Root-Mean-Square Standard Deviation	Maximum Distance from Cluster Seed	Nearest Cluster	Distance to Nearest Cluster	Total telecom services revenue(Current U
1	72	1.046794019	8.0433260935	2	4.0488755304	1410038116.9
2	108	0.5865984355	9.8373259377	1	4.0488755304	242498908.25

Appendix D. Decision tree of CA



Appendix E. Decision rules of CA

```
IF  Annual telecom investment(Current US $ per telecom worker)
   <              $9,610
THEN
  NODE    :       2
  N       :     110
  2       :   96.4%
  1       :    3.6%

IF                $9,610 <= Annual telecom investment(Current US $ per
        telecom worker)
THEN
  NODE    :       3
  N       :      70
  2       :    2.9%
  1       :   97.1%
```

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