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EVALUATION OF REGIONAL EFFICIENCY DISPARITIES BY EFFICIENT FRONTIER ANALYSIS

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Abstract. *The nonparametric methods, such as data envelopment analysis, free disposal hull and order-a frontier analysis, have been applied in this study to evaluate the efficient frontier which extends the application of the production function of regions. These mathematical programming methods allow evaluating the effectiveness of the regional spatial aspects. In recent studies, efficient frontier methods are applied to evaluate regional policy issues of the European Union.*

The purpose of this article is to present a more detailed evaluation of regional disparities by analysing regional infrastructure, human capital efficiency, and linkages among the regions. The application of frontier methods reveals their feasibility for studying regional inputs and outputs to asses a more detailed and more reasonable allocation of funds among Lithuanian regions. A more detailed territorial breakdown is selected in this paper to identify a wider scale of efficiency differences among the regions. From the practical point of view and according to the results, more balanced planning tools are suggested for fund allocation decisions in Lithuanian regions while planning infrastructure and human capital development. As efficient regions are identified, it is recommended to invest in more indirect factors to enhance regional growth. while in inefficient regions more emphasis should be made on more direct interventions to foster economic activity because current investments give insufficient returns. The present type of research is a case study.

Key words: *regional disparities, regional efficiency, economic development, spatial data envelopment analysis, nonparametric analysis*

Introduction

Nowadays, there are economic and social disparities among the European regions. The Insufficient economic growth and a low per capita income of developing regions remain the most significant economic policy issues (ESPON, 2012; Okubo, 2012; Butkus, Matuzevičiūtė, 2011). Hence, regional convergence has remained a key objective of the EU regional policy.

In the time of economic recession and the period of recovery when there is a lack of funds, effective allocation of funds among different territories and the analysis of regional disparities are among the main issues of the European Union regional policy for the programming period 2014–2020 and also for scientific research literature. Different

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methods for decision support of regional allocation of financial funds are evaluated; for instance, Li and Cui (2008) provided insights for resource allocation by applying an inverse form of data envelopment analysis and an extra resource allocation algorithm, Castells and Sole-Olle (2005) analysed the efficiency-oriented distribution of public investments among regions, which revealed the elasticity of infrastructure investments into regions' income according to government insights.

The spatial frontier analysis has become a powerful quantitative and analytical tool for measuring and evaluating performance in various fields. Several studies have been done in the field of spatial frontier analysis to evaluate a country's regional efficiency in its usage of capital and other resources (Autant-Bernard, LeSage, 2011, Schaffer et al., 2011, Galinienė, Dzemydaitė, 2012). This paper follows these notions as spatial frontier methods are applied to evaluate regional performance in the field of infrastructure and region-specific human capital development for Lithuanian NUTS3 territories.

The purpose of this article is to present a more detailed assessment of regional efficiency disparities in the field of regional production technology. Full and partial frontier methods, such as data envelopment analysis, free disposal hull and order-α-quantile analysis, are generalized in this paper and applied for the case of Lithuanian NUTS3 regions. The case of multiple inputs is analysed.

According to the results, proposals for improvements of regional decision support and planning tools are generalized.

1. Related works of efficient frontier analysis

Efficient frontier analysis methods are mathematical programming optimization tools used to measure the technical efficiency of multiple-input and/or multiple-output cases by constructing a relative score of technical efficiency. An efficient frontier analysis expands the application of production function, as the concept of an efficient boundary is evaluated. The explanation of productivity differentials is very important to identify the economic conditions that create inefficiency, and to improve performance (Daraio, Simar, 2007b). The main purpose of productivity analysis studies is to evaluate numerically the performance of a certain number of decision-making units from the point of view of technical efficiency, i.e. their ability to operate close to or on the boundary of their production set (Dariou, Simar, 2007a).

The most commonly used method of an efficient frontier evaluation is data envelopment analysis (DEA). This method was introduced by Charnes, Cooper, Rhodes (1978) and was extended by Banker, Charnes, Cooper (1984) by including variable returns to scale. Data envelopment analysis is a nonparametric method, and its results are determined without making a choice of a parametric model for the production function (Schaffer et al., 2011).

Data envelopment analysis is considered a research which synthesizes the management science, operational analysis methods, and the techniques of econometrics (Wei, 2001). Due to this feature and also the practical functionality of data envelopment analysis, this method became widely used in the field of possible efficiency improvements of decision-making units (DMUs) in governmental, non-profit or private sectors.

The free disposal hull (FDH) is a more general version of a data envelopment analysis estimator as it relies only on the free disposability assumption and does not restrict itself to convex technologies. Therefore, a wider set of data is needed for the frontier analysis to be significant and informative. Both data envelopment analysis and free disposal hull methods are full-frontier ones and are applied to find the uppermost technical efficiency of decision-making units (Daraio, Simar, 2007a).

The first studies of regional frontier analysis were done in 1986–1987 to evaluate the economic performance of Chinese and Japanese cities. The data envelopment analysis was applied as a quantitative and analytical tool. Afterwards, an exponential number of methodological and applied works was published. For example, about 1,500 data envelopment analysis references were reported in Cooper, Seiford, and Tone (2007) in various fields of study to evaluate the performance of data making units in the public sector, educational departments, health care and business environments. This trend was influenced by the empirical orientation of data envelopment analysis and the absence of a need for a lot of a priori assumptions that accompany other methods, for example, a statistical regression analysis.

More recent regional studies are related to regional policy issues of the European Union, an efficient distribution of funds among the regions, and an efficient frontier of the usage of social and infrastructure capital. Some researches have been done in the field of knowledge spillover. For example, Autant-Bernard and LeSage (2011) have estimated a knowledge production function in their research. Spatial spillovers of French regions associated with private and public expenditures were analyzed by applying industry-specific and regional data. It was revealed that the largest direct and indirect effects were influenced by private research and development activities that spilled across industry boundaries.

Broekel et al. (2010) investigated the relation between cooperation and the innovative success of German regions. The non-convex order-m frontier method was used. The research provided a new evidence on the relationship between regional innovation efficiency and levels of regional cooperation by the application of data on the co-application and co-invention of patents for German labor market regions. The effect of cooperation was analyzed. Such approach allowed the relationship between a set of knowledge inputs and a set of innovative outputs to vary among the regions.

Zhong et al. (2011) investigated the effectiveness of research and development investments by applying data envelopment analysis models and evaluated the relative efficiencies of regional investments. The cases of constant and variable return to scale were evaluated for an input-oriented model. The results revealed that there were no Chinese regions that exhibited an increasing return to scale. The results of data envelopment analysis indicated that a more diverse policy should be considered.

TABLE 1. **The related works of application of nonparametric frontier methods for regional studies**

Tields of the research	Researchers
Comparative studies on the economic performance and productivity of Chinese and Japanese cities	Seifert, Zhu (1998); Hashimoto, Ishikawa (1993)
Quantifying knowledge spillovers and technological connections among the regions	Broekel et al. (2010); Autant-Bernard, LeSage (2011); Zhong et al. (2011)
Regional allocation of infrastructure investments, regions' efficiency analysis with a given set of human resources, infrastructure capital and other indicators	Castells, Sole-Olle (2005); Li, Cui (2008); Schaffer, Siegele (2009); Schaffer (2011); Schaffer et al. (2011); Galinienė, Dzemydaitė (2012)
Advanced forms of traditional data envelopment analysis, including partially frontier methods of order-α quantile, order-m analysis, conditional data envelopment analysis	Daouia, Simar (2007a); Daouia, Simar (2007b); Simar, Wilson (2008); Jeong et al. (2010); Simar, Zelenyuk (2011); Tauchman (2012)

Another set of studies has been done in the field of resources and allocation of funds among regions. Castells and Sole-Olle (2005) analysed the efficiency-oriented distribution of public investments among regions, which revealed the elasticity of infrastructure investments to regions' income according to government insights. The equation was estimated with a panel of data on investment and capital stock of transportation infrastructure, such as roads, rails, airports, for the Spanish regions. It was shown that a scale of the regional efficiency made only a limited impact on the geographical distribution of government's infrastructure investment.

Schaffer et al. (2011) analyzed indirect factors that foster regions' attractiveness for private investors, i.e. transport infrastructure and human capital indicators. An outlier robust extension of data envelopment analysis and regression analysis were applied to decompose the efficiency of German regions. The findings implied that the regions' efficiency was driven not only by the spatial but also by the structural factor. A more differentiated funding scheme for the regional infrastructure in respect to both structural and spatial factors was suggested in the paper.

Li and Cui (2008) constructed an algorithm by using data envelopment analysis tools in various model forms and extensions, such as a variable return to scale, an inverse form of data envelopment analysis techniques, and an extra resource allocation algorithm, to provide recommendations for resource allocation and to propose possible alternatives for achieving an effective equality-efficient target. Halkos, Tzeremes (2013) analysed regional productivity effects on the countries' environment according to the Kyoto protocol by applying conditional data envelopment analysis and the free disposal hull method.

Some studies have been done to evaluate the regional transport infrastructure and human capital factors (e.g., Schaffer, Siegele (2009), Schaffer (2011)). The infrastructure capital is considered an important factor to enhance the potential level of regional production and income. These notions are applied to the case of Australian and German regions in the field of public transport infrastructure. For the case of Lithuania, regional transport infrastructure and regional connectivity were analysed by applying the data envelopment analysis (Galinienė, Dzemydaitė, 2012) to find their effects on regional growth and efficiency disparities. Human capital and infrastructure indicators as well as output expressed by gross domestic product per capita were analyzed. The comparatively inefficient Lithuanian regions were identified according to the efficient boundary of production technology.

In recent studies, more advanced forms of efficient frontier are analysed. Daraio and Simar (2007b) developed a conditional frontier model which incorporated the external-environmental variables in nonparametric frontier models for convex and nonconvex technologies. The conditional data envelopment analysis was introduced. The external-environmental variables were explained as neither inputs nor outputs under the control of a data making unit. This model was proposed to measure the efficiency of production in a fully nonparametric setup. Jeong et al. (2010) provided an asymptotic of the conditional full disposal hull and conditional data envelopment analysis and outlined the use of these estimators from the theoretical perspective to supplement the efficiency patterns with the underlying production process.

Simar and Zelenyuk (2011) extended the model of data envelopment analysis and the technique of free disposal hull by introducing noise into nonparametric frontier models. This type of analysis is suitable for modeling the marginal effects on the inefficiency level jointly with the estimation of marginal effects of input. The approach is robust to heteroskedastic cases and to unknown distributions of statistical noise. The method improved the data envelopment analysis and free disposal hull estimators by allowing them to be robust to statistical noise and the outliers. The procedure was tested by various simulated cases and was also illustrated for some real data sets.

The partial frontier methods, such as order-α analysis and order-m frontier, were introduced, which helped to go through sensitivity problems of the data set in the traditional data envelopment analysis (Daouia, Simar, 2007a; Simar, Wilson, 2008) and to increase the significance of the performed analysis. The main improvement in the partially frontier methods was that super-efficient data making units were located beyond the production-possibility frontier. According to that, partially frontier methods enveloped a sub-sample of the data. This helped to increase the confidence in the analysis based on the evaluation of the nonparametric frontier models (Tauchman, 2012).

According to the literature research of data envelopment analysis methods, it is obvious that this type of analysis is a powerful analytical and also quantitative tool for measuring regional performance in various aspects, as well as for the evaluation of current policy issues of the European Union. According to its empirical orientation and results linked to the level of efficiency, the empirical analysis gives benchmarks for more detailed funding schemes among the regions connected to the input and output factors.

2. Model for the evaluation of regional efficiency disparities

In production theory and efficiency analysis, the locus of the maximal attainable level of the output (production) is estimated given a set of inputs (production factors) (Daouia et al, 2012). Nonparametric frontier methods expand the application of the production function while analyzing the case of multiple inputs and multiple outputs. It is assumed that regional efficiency is improved more likely by growing outputs rather than decreasing inputs because of the nature of the infrastructure capital and the human capital (Schaffer et al., 2011). Therefore, an output-oriented version of a model is used.

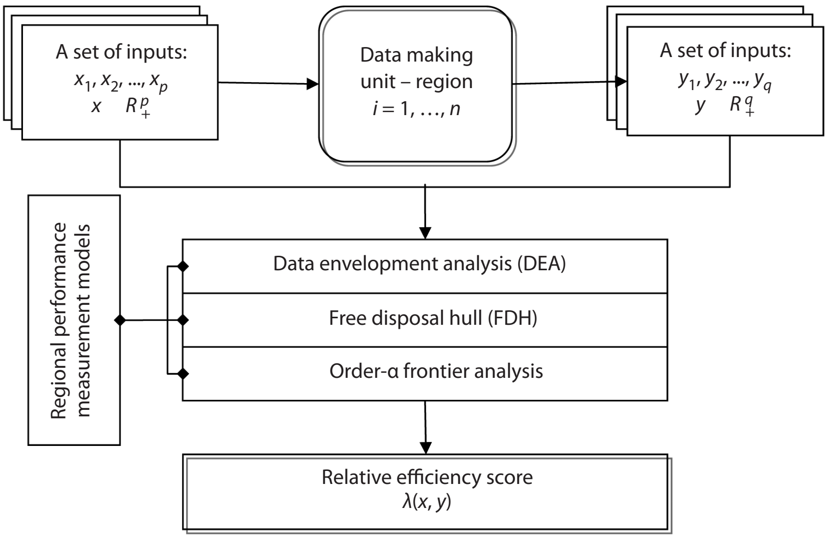

FIG. 1. **Conceptual framework for the regional performance measurement.**

In this paper, the order-α frontier method is applied together with the data envelopment analysis and free disposal hull to determine their applicability for evaluating the Lithuanian regional efficiency. The data envelopment analysis and free disposal hull are applied as full frontier unconditional methods, while the order-α frontier is a partially frontier method. For the research, a set of different frontier methods is chosen in order to evaluate the appropriate tools for the Lithuanian regional analysis and for the evaluation of the relative efficiency scores of data making units.

The relative efficiency score reveals by how much output quantities can be proportionally expanded without altering the inputs used (Schaffer et Al., 2011). The term "non-parametric" is not meant to imply that the methods lack parameters, but that the number and nature of the indicators are not fixed in advance. The nonparametric frontier models help to consolidate multiple performance measures into an efficiency score without having to define the complex relationships among the indicators (Kuah et al., 2012).

The estimation of regional efficiency follows the techniques of data envelopment analysis. The selection of data making units, the explanation of inputs and outputs, and the formulation of the model are considered. The enhanced data envelopment analysis is described in full by Daouia and Simar (2007a). The mathematical formulations (1)–(3) below reflect a reduced version of this model. The formulation (4) explains the efficiency score calculated by a more advanced form of the efficient frontier analysis – the order-α quantile analysis.

Efficient frontier analysis methods

It is considered that every region disposes of a set of inputs $x \in R_+^p$ to produce a set of outputs $x \in R_+^q$ that are positive numbers. Feasible combinations of (x, y) are defined as (Schaffer et al., 2011):

$$\psi = \left\{(x, y) \in R_+^{p+q} \middle| x \; can \; produce \; y\right\}. \tag{1}$$

The boundaries of ψ reflect the maximum outputs which can be generated with given inputs. The regions' efficiency frontier is defined as

$$Y^{\delta} = \left\{(x, y^{\delta}(x)) \middle| y^{\delta}(x) \in Y(x) : \lambda y^{\delta}(x) \notin Y(x), \forall \lambda > 1\right\}. \tag{2}$$

$Y(x)$ means a set of technologically feasible outputs, and $y^{\delta}(x)$ is the maximum achievable output of the unit with the input level x. The efficiency score of a decision-making unit is defined as

$$\lambda(x, y) = sup\left\{\lambda \middle| (x, \lambda y) \in \psi\right\} = sup\left\{\lambda \middle| \lambda y \in Y(x)\right\}. \tag{3}$$

In this formula, $\lambda(x, y) \geq 1$ is the proportionate increase of the output y of the region operating at the output level x for a region to be efficient (Schaffer et al., 2011). To determine the unknown ψ, nonparametric estimators, such as data envelopment analysis and free disposal hull, have been proposed. The free disposal hull and the data envelopment analysis define an efficient boundary according to the highest technically achievable output depending on the performance of decision-making units.

With $S_{(Y|X)}(\lambda y|x)$ defined as the probability $Prob(Y \geq y|X \leq x)$ and $F_X(x)$ as the probability $Prob(X \leq x)$, Daouia and Simar (2007a) define the order-α quantile efficiency score of the output-oriented case for each unit (x, y) $\quad \psi$ as

$$\lambda_\alpha(x, y) = sup\{\lambda|S_{(Y|X)}(\lambda y|x) > 1 - \alpha\}, \ F_X(x) > 0, \ \alpha \quad [0, 1]. \tag{4}$$

In this paper, the order-α frontier analysis is also applied, which allows extreme observations to be above partial frontier at different levels of confidence (α) while finding the efficiency of data making units. Efficiency scores, calculated by free disposal hull technique, are evaluated in the same way as the order-α frontier method with the confidence level α = 1. In data envelopment analysis, the confidence level $\alpha = 1$ is also used.

Input and output indicators

Inputs and outputs in regional frontier analyses generally reflect the socio-economic performance of territorial units. The gross regional product, the intensity of the trade or employment rate can be considered on the output-side of the model (Athanassopoulos, 1996). According to LeSage and Fischer (2008), intensive variables might reflect economic performance in a more appropriate way. This paper follows this notion and defines the output side according to the per-capita gross domestic product for the year 2011.

Presuming that regional endowment with immobile factors is essential to generate regional production (Bronzini, Piseli, 2009), input variables are characterised by a region's transport infrastructure and human capital. With regard to infrastructure capital, the input factor determines the intraregional equipment with transport infrastructure characterised by the intensity of investments in the regional transport infrastructure and the density of local roads in the region. The road density could be weighted by the differences of maintenance and construction cost (Schaffer et al., 2011). The transport infrastructure of a region i (I_i) is determined by the formula:

$$I_i = \frac{r_{w,i}}{a_i}, \tag{5}$$

here $r_{w,i}$ is the length of the road network (in km) weighted by the differences of construction and maintenance cost of a region, i, a_i is the area of region i (in sq. km).

Regional human capital is defined in quantitative and qualitative ways. The quantitative side of human capital is characterized by the absolute number of the available workforce. The size effects of workforce are of interest because they partly reflect the regions' characteristics as metropolitan or rural areas (Schaffer et al., 2011).

According to the Pearson correlation analysis, the absolute number of employees is more significant in the model than the share of employees in the total population. Therefore, the total number of employees is used in the model. The human capital is also evaluated from the qualitative perspective. The qualitative human capital indicator is calculated according to educational achievements of the regional workforce. The formula of a region's human capital indicator (Q_i) is as follows:

$$Q_i = \frac{\sum_{j=1}^{3} \omega_j \cdot f_{ij}}{\sum_{j=1}^{3} f_{ij}}. \tag{6}$$

According to the International Standard Classification of Education (ISED), ω_i is a weighting factor of the educational level. Educational achievements are weighted to 1, 1.8 and 2.6, respectively, according to the average time needed for students and teachers to obtain the qualification (Schaffer et al., 2011), and f_{ij} is the number of workforce.

TABLE 2. **Correlation of input variables with gross regional product per capita**

	Infrastructure capital indicator	Human capital indicators		
		Qualification	Number of employees	Share of employees in the total population*
Correlation coefficient (Pearson)	0.848	0.922	0.902	0.600
Significance	0.002	0.000	0.000	0.067

* The indicator remains unconsidered in the frontier analyses.

The correlation coefficients between the input variables and the output have been evaluated. It is apparent that relationships between the output and input indicators used in the analysis are significant at the 0.01 level (2-tailed). The indicator of the share of employees in the total population is not used in this model because the level of significance does not satisfy the 0.01 or 0.05 level of confidence. In the context of this paper, the evaluated regional efficiency scores only refer to the considered input and output variables, because rather inefficient regions could be efficient in another context.

3. Regions' efficiency evaluation in the usage of infrastructure and human capital: the case of Lithuanian NUTS3 regions

The identification of Lithuanian regions' efficiency follows the mathematical models of order-α frontier analysis, free disposal hull and data envelopment analysis outlined in Section 2. Decision-making units are characterised by a uniform production function to transfer a set of inputs into outputs.

A region is considered comparatively efficient if one or more other regions equipped with a similar or worse level of inputs generate a higher level of outputs (Schaffer et al., 2011). It is considered to be not possible to reduce the input factors, such as human capital or transport infrastructure, in the regional production function. More emphasis is put on the output side of the production function. The output-oriented model is used, so that regions could achieve a higher output level by using their resources more efficiently.

There are several nonparametric estimators used to evaluate regional efficiency. Full frontier estimators, such as free disposal hull and data envelopment analysis, are rather sensitive to extreme observations and outliers because they envelope all data points of the observed set (Daraio, Simar, 2007a). Data envelopment analysis must satisfy the presumptions of convex technologies and free disposability.

More robust estimators, such as partial order-α frontier and order-m analysis, solve the sensitivity problem of DEA and FDH models because, instead of defining the efficient boundary according to the uppermost achievable output, extreme observations are allowed to be above a partial frontier in the case of a multivariate setup (Daouia, Simar, 2007a). In partial frontier models, the efficient frontier does not reflect the maximum achievable output, but some outliers are allowed to be above the frontier.

In this paper, the convexity of Lithuanian regional data is evaluated by analysing the distribution of efficiency scores by using different levels of confidence in the frame of the order-α analysis. The idea behind the order-α quantile-type frontier is to determine the frontier by fixing first the probability $(1 - \alpha)$ of the observing points above this order-α frontier (Daraio, Simar, 2007a). The results of the analysis are partly dependent on the choice of α.

TABLE 3. **Order-α efficiency score of Lithuanian NUTS3 regions, 2011**

Decision-making unit	**α = 0.80**	**α = 0.85**	**α = 0.90**	**α = 0.95**	**FDH (α = 1)**
Alytus region	1.125541	1.134199	1.134199	1.134199	1.134199
Kaunas region	1	1	1.110465	1.110465	1.110465
Klaipėda region	**0.688482**	1	1	1	1
Marijampolė region	1	1	1	1	1
Panevėžys region	1	1	1	1	1
Šiauliai region	1	1	1	1	1
Tauragė region	1	1	1	1	1
Utena region	**0.762475**	**0.762475**	1	1	1
Vilnius region	1	1	1	1	1
Average efficiency	**0.9529**	**0.9885**	**1.027**	**1.027**	**1.027**

Compiled by the authors according to the data of the Department of Statistics of the Republic of Lithuania.

As is evident from the order-α efficiency scores of the Lithuanian NUTS3 regions (Table 3), the Utena region is super-efficient at a confidence level of 85 with a set of given inputs; the Klaipėda and Utena regions are super-efficient at a confidence level of 80. This analysis reveals that there are two regions – Klaipeda and Utena – that could be considered as super-efficient with a given set of inputs, – but comparatively low level of confidence means that these differences between efficient and super-efficient regions are not so big and there are no extreme values in the input data set at a level of $\alpha = 0.90$, 0.95 or 0.99. According to these results, the full frontier methods, such as the data envelopment analysis, could be applied to convex data and the evaluation of regional efficiency.

If we compare full frontier methods, the data envelopment analysis is more appropriate than the traditional free disposal hull. If we use FDH, only two regions – Alytus and Kaunas – are inefficient. All the other regions are considered to be efficient; their efficiency scores are equal to 1. This analysis is not very informative for Lithuanian regions, because FDH is based on the notion that each decision-making unit is only benchmarked against units with similar or lover input levels. A unit is considered inefficient if its peers generate a higher level of outputs. If a data making units' input equals to the minimum level, it cannot be dominated by the unit with a lower input level, and this unit is considered to be efficient in generating the outputs (Schaffer et al., 2011).

As Lithuania is a small country and there are not a lot of observations, the data envelopment analysis is more informative in the nonparametric efficiency analysis because FDH relies on a minimal set of assumptions and requires a larger data set. The DEA envelopes all the data points and give the efficiency scores by evaluating the most efficient decision-making units (Daraio, Simar, 2007a). Each DMU is compared to an efficient boundary according to the highest technically achievable output according to all the DMUs; therefore, the higher number of observations is then compared in the FDH analysis.

The most efficient regions are detected by following the model of data envelopment analysis. These regions are Vilnius, Klaipėda, Marijampolė, and Utena. These regions are situated on the efficient frontier that identifies the same efficiency with the given level of human capital and infrastructure resources (Fig. 2). Even though the income per capita is comparatively low in the Marijampolė and Utena regions (lower than the Lithuanian average), these regions with modest inputs generate comparatively high levels of output compared with other Lithuanian regions.

The highest efficiency achieved in the Vilnius, Klaipėda, Utena, and Marijampolė regions reveals that the possible production frontier is reached with the current human capital and infrustructure capital indicators. Even though the Marijampolė and Utena regions that generate lower than average gross domestic product per capita, they are considered to use even limited regional resources in a more efficient way than do other Lithuanian regions. To enhance regional growth in these regions, more emphasis should be put on indirect programs for human capital development, enchancement of current

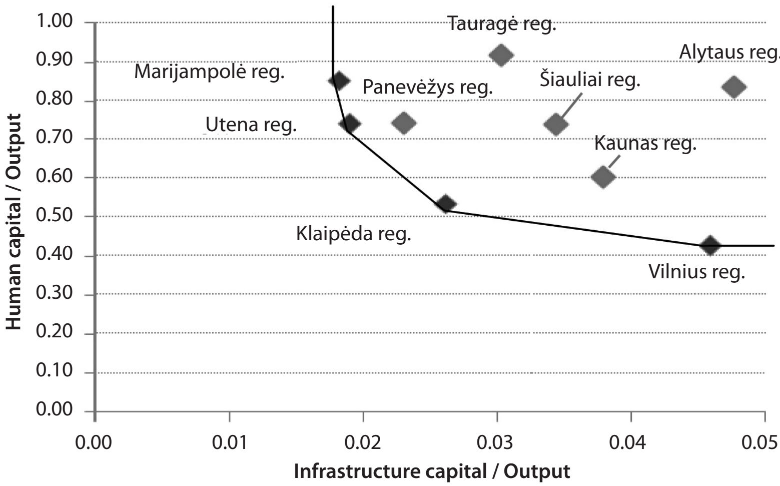

FIG. 2. **Nonparametrically estimated production possibility frontier (isoquant) of Lithuanian NUTS3 regions by application of DEA**

(compiled by the authors according to the data of the Department of Statistics of the Republic of Lithuania)

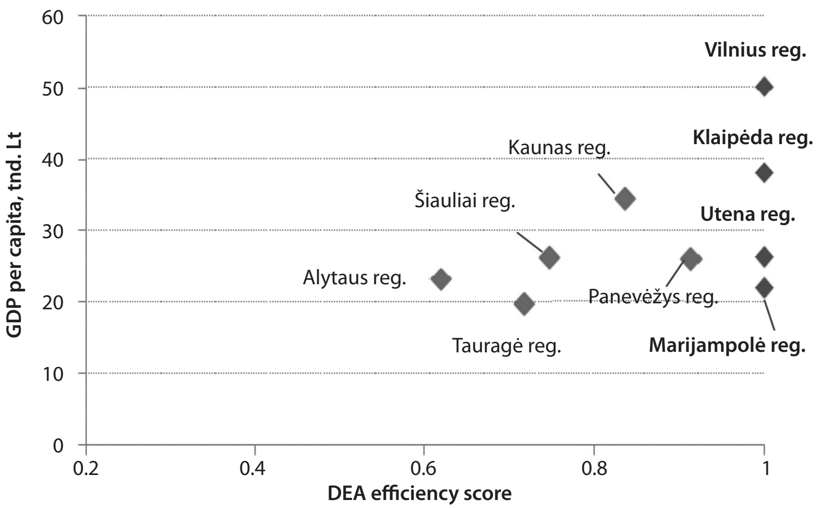

FIG. 3. **Efficiency scores of Lithuania NUTS3 regions, 2011**

(compiled by the authors according to the data of the Department of Statistics of the Republic of Lithuania) qualifications, attraction of more workforce and also for improvements in transport infrustructure because the ”bottleneck“ of using these resources is reached.

Compared to the results of the recent Lithuanian NUTS3 regional efficiency analysis of 2010 (Galinienė, Dzemydaitė, 2012), the Vilnius, Kaunas and Utena regions have emerged as efficient even though the analysis was focused more on the external transport infrustructure factor and connectivity among the regions. These results indicate that, as mentioned above, more indirect programs are recommended for the Vilnius, Klaipėda, and Utena regions in order to increase regional growth.

According to data envelopment analysis, the most inefficient Lithuanian NUTS3 regions are those of Alytus, Tauragė, and Šiauliai. The efficiency scores in the usage of infrastructure capital and human capital are the lowest among all the data making units. According to the model, these regions could enhance the gross regional product by using inputs more efficiently and achieve the output levels of 26.4, 19.8, and 29.39, respectively, with the current infrastructure and a specific-human capital of a region. The enhancement with the current resources could also be reached in the Kaunas and Panevėžys regions which are more efficient than the regions of Alytus, Šiauliai, and Tauragė.

These estimates indicate that more direct programs should be implemented in order to attract private investments to the regions and to increase the productivity level of regional entities. It is not argued that funds for transport infrastructure or human capital qualifications should be banned, but it is suggested that direct programs to foster regional activity are more important for regional economic growth with current resources. More emphasis should also be put on increasing export possibilities of the regional companies because they have the potential to use their production capacity in a more intensive way (Dzemydaitė et al., 2012).

As regions are different in size, input and output characteristics, the peer data making units are evaluated for each inefficient region. Accordingly, efficient output values of inefficient regions are projected. For example, the Kaunas regional production technology has most similarities with the Klaipėda region (77 per cent of similarity) and the Vilnius region (23 per cent of similarity); therefore, Klaipėda and Vilnius are efficient peers to the Kaunas region; the Panevėžys region is the most similar to the Marijampolė region (60 per cent of similarity); other regions that are similar are Klaipėda (32 per cent) and Utena (8 per cent). Analogically, most similar DMUs have been also evaluated for other regions. If we evaluate the model from the isoquant view, the projected efficient values of inputs (per GPD) move forward the efficient frontier, and the peer values define where the relevant coordinates of the frontier are.

Conclusions

The overview of scientific literature emphasises the need to support decisions regarding the allocation of funds among European regions, because the divergence among the regions is not decreasing and there is a lack of available funds. Nonparametric mathematical programming tools are used to measure technical efficiency in different fields of study such as the usage of the transport infrastructure, knowledge spillovers, and human capital efficiency.

From all the efficient frontier estimators, the traditional data envelopment analysis is most commonly applied in the scientific researches, even though new forms of DEA have been developed. As data envelopment analysis is restricted to convex technologies, three estimators of the efficient frontier are evaluated in this paper for the case of Lithuanian NUTS3 regions. The regional efficiency scores are calculated by applying different confidence levels in the frame of the order-α quantile analysis to find the confidence level at which superefficient regions could be evaluated.

The analysis has revealed that there are two regions that could be considered as super-efficient with a given set of inputs – the regions of Klapėda and Utena, but a comparatively low level of confidence ($\alpha = 0.80$ and $\alpha = 0.85$) means that there are no intense differences between the efficient and the super-efficient regions and that there are no extreme values in the input data set at a level of $\alpha = 0.90$, 0.95 or 0.99. Accordingly, it is stated that the full frontier methods, such as data envelopment analysis, could be applied to convex data and for evaluating regional efficiency.

The data envelopment analysis is more informative for Lithuanian NUTS3 regions when comparing data envelopment analysis with a free disposal hull because the data set is comparatively small. Free disposal hull is supported by the notion that each decision-making unit is only benchmarked against units with a similar or lower level of inputs; therefore, if the inputs of the region equal the minimum level, they are considered to be efficient in generating outputs. Accordingly, inefficient regions are not identified properly.

By applying data envelopment analysis, an efficient boundary (isoquant) is identified. Four regions – Vilnius, Klaipėda, Utena and Marijampolė – are considered on the efficient frontier. Even though the regions of Utena and Marijampolė have a lower than average GDP per capita, these regions are considered to be technically efficient in production by using current and even limited levels of inputs.

The model helps to evaluate not only inefficient DMUs, but also to project the possible outputs according to the efficient peers (DMUs) which have the most comparable sets of inputs among the efficient ones. For example, the Kaunas regional production technology is most similar to that of the Klaipėda and Vilnius regions (77 and 23 per cent of similarity, respectively). The Panevėžys region is most similar to the Marijampolė (60 per cent of similarity) and other regions, such as those of Klaipėda and Utena (32 and 8 per cent respectively).

From the practical point of view, the estimation of the Lithuanian NUTS3 regions' efficient frontier helped to formulate the benchmarks for regional development. It has revealed that efficient regions, such as Vilnius, Klaipėda, Utena, and Marijampolė, should put more emphasis on the indirect programmes of the economic development to increase the human capital and transport infrastructure development and to attract capital flows to these regions because "the bottleneck" of inputs' usage has been reached.

In comparatively inefficient regions, such as Alytus, Tauragė, Kaunas, Šiauliai, Panevėžys, different programs should be implemented. More emphasis should be put on direct economic activity programmes to improve economic activity because current resources could be used much more efficiently.

Even though the efficient frontier estimators are appropriate for regional efficiency studies, these methods remain limited as to the choice of input and output indicators because other indicators in the other fields of study and inefficient regions could indicate better results.

REFERENCES

Athanassopoulos, A. D. (1996). Assessing the comparative spatial disadvantage (CSD) of regions in the European Union using non-radial data envelopment analysis methods. Journal of Operational Research, Vol. 94, pp. 439–452.

Autant-Bernard C., LeSage J.P. (2011). Quantifying knowledge spillovers using spatial econometric models. Journal of Regional Science, Vol. 5, No. 3, pp. 471–496.

Banker, R.D., Charnes, R.F., Cooper, W. W. (1984). Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. Management Science, Vol. 30, pp. 1078–1092.

Bronzini, R., Piselli, P. (2009). Determinants of Long-Run Regional Productivity with Geographical Spillovers: The Role of R&D, Human Capital and Public Infrastructure. Regional Science and Urban Economics, Vol. 39, pp. 187–199.

Broekel, T., Buerger, M., Brenner, T. (2010) An investigation of the relation between cooperationand the innovative success of German regions. Papers in Evolutionary Economic Geography.10.11, Utrecht University, Utrech.

Busillo F., Pellegrini G., Terribile F., Tarola O., Muccigrosso T. (2012). Measuring the effects of European Regional Policy on economic growth: A regression discontinuity approach. *Papers in Regional Science* [interactive], http://onlinelibrary.wiley.com/doi/10.1111/j.1435-5957.2012.00459.x/pdf, accessed on: 10 06 2013.

Butkus M., Matuzevičiūtė K. (2011). Ekonomikos teritorijų (regionų) skirtumų vertinimas Europos sąjungos šalyse. Ekonomikos vadyba: aktualijos ir perspektyvos, Vol. 3, Nr. 23, pp. 66–79.

Castells, A., Sol´e-Oll´e, A. (2005). The regional allocation of infrastructure investment: The role of equity, efficiency and political factors. *European Economic Review,* Vol. 49, pp. 1165–1205.

Charnes A., Cooper, W. W. Rhodes, E. (1978). Measuring the efficiency of decision making units. European Journal of Operational Research, Vol. 2, No. 4, pp. 429–444.

Cooper,W. W., Seiford, L. M., Tone, K. (2007). *Introduction to Data Envelopment Analysis and Its Uses: With DEA-solver Software and References.* Berlin: Springer.

Daouia, A., Florens, J. P., Simar, L. (2012). Regularization of nonparametric frontier estimators. Journal of Econometrics. Vol. 168, No. 2, pp. 285–299.

Daouia, A., Simar, L. (2007a). Nonparametric efficiency analysis: a multivariate conditional quantile approach. Journal of Econometrics, Vol. 140, pp. 375–400.

Daouia, A., Simar, L. (2007b). Conditional nonparametric frontier models for convex and nonconvex technologies: a unifying approach. Journal of Productivity Analysis, Vol. 28, No. 1–2, pp. 13–32.

Dzemydaitė, G., Dzemyda, I., Jurgelevičius, A. (2012). Evaluation of implementation of national export development strategy: case study of the republic of Lithuania. Intellectual Economics, Vol. 6, No. 1, pp. 776–797.

ESPON (2012). Factsheet Latvia–Lithuania. ESPON Project TERREVI.

European Commission (2011), Regional Policy – Regional economic policies, Lithuania 2007–2013 [interactive], http://ec.europa.eu/regional_policy/country/prordn/index_en.cfm, accessed on: 15 04 2013.

Galinienė, B., Dzemydaitė, G. (2012). Spatial data envelopment analysis method for the evaluation of regional infrastructure disparities. Social Technologies. Vol. 2, No. 2, pp. 390–403.

Halkos, G. E., Tzeremes, N. G. (2013). Measuring the effect of Kyoto protocol agreement on countries' environmental efficiency in CO_2 emissions: an application of conditional full frontiers. Journal of Productivity Analysis. [interactive] h*ttp://link.springer.com/article/10.1007/s11123-013-0343-1/fulltext.html* accessed on: 10 05 2013.

Hashimoto, A., Ishikawa, H. (1993). Using DEA to evaluate the state of society as measured by multiple social indicators. Socio-Economic Planning Sciences, Vol. 27, pp. 257–268.

Jeong, S., Park, B. U., Simar, L. (2010). Nonparametric conditional efficiency measures: asymptotic properties. Annals of Operations Research, Vol. 173, No. 1, pp. 105–122.

Kuah, C. T., Wong, K. Y., Wong, W. P. (2012). Monte Carlo Data Envelopment Analysis with Genetic Algorithm for Knowledge Management performance measurement. Expert Systems with Applications, Vol. 39, No.10, pp. 9348–9358.

LeSage, J. P., Fischer M. M. (2008). Spatial Growth Regressions: Model Specification, Estimation and Interpretation. Spatial Economic Analysis, Vol. 3, No. 3, pp. 275–304.

Li, X., Cui, J. (2008). A comprehensive DEA approach for the resource allocation problem based on scale economies classification. Journal of Systems Science and Complexity, Vol. 21, No. 4, pp. 540–557.

Ocubo T. (2012). Antiagglomeration subsidies with heterogeneous firms. Journal of Regional Science. Vol. 52, No. 2, 2012, pp. 285–287.

Schaffer, A. (2011). Appropriate policy measures to attract private capital in consideration of regional efficiency in using infrastructure and human capital. Working Paper Series in Economics, No. 31 [interactive] http://hdl.handle.net/10419/48855 accessed on: 10 05 2013.

Schaffer, A., Siegele, J. (2009). Efficient use of regional transport infrastructure, communication networks, and human capital. Journal of Infrastructure Systems, Vol. 15, No. 4, pp. 263–272.

Schaffer, A., Simar, L., Rauland, J. (2011). Decomposing regional efficiency, Journal of Regional Science*, Vol. 51, No 5, pp. 931–947*

Seifert, M. L., Zhu, J. (1998). Identifying excesses and deficits in Chinese industrial productivity (1953-1990): A weighted data environment analysis approach. Omega, Vol. 26, No. 2, pp. 279–296.

Simar, L., Wilson, P. W. (2008). Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models. Management Science, Vol. 44, pp. 49–61.

Simar, L., Zelenyuk, V. (2011). Stochastic FDH/DEA estimators for frontier analysis. Journal of Productivity Analysis, Vol. 36, No. 1, pp. 1–20.

Statistical data of Lithuania NUTS3 regions for 2011. The Department of Statistics of the Republic of Lithuania.

Tauchman, H. (2012). Partial frontier efficiency analysis. Stata Journal, Vol. 12. No. 3, pp. 461–478.

Wei, Q. (2001). Data envelopment analysis. Chinese Science Bulletin. Vol. 46, No. 16, pp. 1321–1332.

Wu, J. (2010). Economic fundamentals and urban-suburban disparities. Journal of Regional Science, Vol. 50, No. 2, pp. 570–591.

Zhong, W., Yuan, W., Li, X. S., Huang, Z. (2011). The performance evaluation of regional R&D investments in China: An application of DEA based on the first official China economic census data. Omega, Vol. 39, No. 4, pp. 447–455.