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Estimation of environmental efficiencies of economies and shadow prices of pollutants in countries in transition

Mykhaylo Salnykov
Valentin Zelenyuk

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Various measures of technical efficiency, such as output distance function, input distance function and directional distance function can be used as sustainability indicators in the case when some outputs produced are undesirable, such as pollution. Shadow prices of environmental pollution asses short run perspectives of increase in pollution when desirable output is increased and may serve as a reference value for environmental taxes and prices for international emission trade. We make an attempt to estimate environmental efficiencies of countries (based on the output distance function with general directional vector) as well as shadow prices for selected pollutants (CO_2, SO_2 and NO_x). Two alternative estimation approaches are employed: parametric (Translog specification) and nonparametric (DEA). Statistical characteristics of the obtained parametric estimates are assessed using the smooth homogeneous bootstrap technique. Our results indicate that, on average, countries value pollutants proportionally to their direct impact on human health (*i.e.* the most hazardous pollutants have the highest shadow prices). We find that in general both rich and poor countries can be fully environmentally efficient, while most of the countries in transition (CITs) turned out to be inefficient. Our findings imply that under emission permit trade agreements CITs will generally be permit sellers. By selling permits they will hamper their future ability of economic growth, thus some restrictions (which we propose) must be made in such agreements to limit their unsustainability for CITs. Our estimates show that currently global wealth and pollution are allocated inefficiently. We determine that different estimation techniques provide with statistically different estimates. The work provides with illustrative examples of using the estimates to draw forecasts on environmental effect of economic growth; to determine price range on international pollution permit markets and to estimate economically justified rates of environmental taxation. Finally, we provide policy implications and outline potential directions for the future studies in the field.

Keywords. Pollution, environmental efficiency, shadow prices, bootstrap, countries in transition, parametric and nonparametric techniques, bootstrap.

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Mykhaylo Salnykov
Department of Economics, Simon Fraser University
and UPEG at EROC-EERC-Kyiv
E-mail: msalnykov@eerc.kiev.ua, msalnyko@sfu.ca

Valentin Zelenyuk
Institut de Statistique, Université Catholique de Louvain
and UPEG at EROC-EERC-Kyiv

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LIST OF ABBREVIATIONS

A1–A13	Axiom 1 through 13
BC	Bias corrected
CITs	Countries in transition
CO_2	Carbon dioxide
DEA	Data envelopment analysis
DMU	Decision making units
DV	Directional vector
ER	Efficiency rule
ESI	Environmental Sustainability Index
IDF	Input distance function
NIRS	Non-increasing returns to scale
NO	Nitric oxide (nitrogen monoxide)
NO_2	Nitrogen dioxide
NO_x	Nitrogen oxides
NYSDEC	New York State Department of Environmental Conservation
ODDF	Output directional distance function
ODF	Output distance function
OHE	Output oriented hyperbolic efficiency measure
PPF	Production possibility frontier
PPP	Purchasing power parity
SD	Sustainable development
SFA	Stochastic frontier analysis
SO_2	Sulfur dioxide
SO_3	Sulfur trioxide
VRS	Various returns to scale
WB	World Bank
WCED	World Commission on Environment and Development
WEF	World Environmental Forum
WRI	World Resource Institute

1. INTRODUCTION

At the modern age characterized by an unprecedented technological breakthrough, the humankind still cannot develop a single technological process producing only desirable products. These outputs vary from fully materialistic, such as pollution from industrial production, to the abstract, such as moral degradation from production of pornography. The undesirable outputs yield negative revenue (*i.e*. cost), since otherwise they would be desirable as any by-product produced at no cost but yielding a revenue, hence increasing a profit. These costs can be carried by the producers, but mostly they are transferred to a third party, in which case we deal with external costs of undesirable products.

Mr. Arthur Cecil Pigou (1948) proposed a simple idea to avoid such transfer in the case of environmental pollution by introducing taxation equal to the marginal external cost: in this case only a part of the external cost is transferred to the society while the other part lies on the producer. Unfortunately, in many cases it is very hard (if possible) to measure the external cost, since no markets for undesirable outputs exist.

An alternative interpretation of Pigou's idea claims that efficient environmental degradation may be achieved by establishing a market for pollution with the prices set using shadow price of the externality as a reference value (Faber and Proops, 1991; Färe *et al*., 1993).

The present work extends the aforementioned ideas by proposing an alternative to the existing methods of environmental valuation by relying on shadow prices of environmental pollutants. These shadow prices are considered *the internal valuation of environmental degradation* (*connected to each pollutant*) *by a given society*.[1] Having such intuition of them, it will be possible to estimate how high environmental damage is valued by a society. These prices provide justified reference values of environmental taxation and international environmental trade prices (Färe *et al*., 1993) (*e.g*., under Kyoto protocol). They may also propose a solution of a previously unsolvable problem of environmental demand function construction and calculating so called 'green GDP', an environmental analogue of economic GDP, which accounts for the value of environmental pollution (Hueting, 1991).

In the process of the shadow prices estimation we will also estimate an environmental efficiency measure., which is an alternative to the numerous sustainability indicators (de Koeijer *et al*., 2002): many of them consider either purely bio-ecological (*e.g*., Pannell and Glenn, 2000) *or* purely socio-economic component of sustainability (*e.g*., Smyth and Dumanski, 1993). Our indicator, in contrast, will look upon *both* aspects of sustainability, *i.e*. how environmentally sustainable the economy is given its economic development.

[1] The intuition of shadow prices will be discussed in Section 3, while mathematical formalization of this concept will be developed in Section 4.

It must be emphasized, however, that despite the fact that many previous works have discussed the importance of implication of shadow prices and efficiency measurements, all of them we are aware of were measuring efficiencies and shadow prices of pollution for separate plants within an industry (mostly pulp and paper). In contrast, the present study looks on the country level; to our knowledge, it is the first attempt to apply the methodological approach of environmental production microeconomics to the issues of environmental macroeconomics and public policy. In addition, it is the first time such environmental efficiencies and shadow prices of pollutants are estimated for the countries in transition (CITs).

The main research question of the study is: '*How* inefficient are individual countries and *What* is the internal valuation of environmental pollution by these countries?'

The work will also attempt to answer a number of additional questions. These include but are not limited to:

- How far are individual countries from their technological potential, *i.e*. by how much it is possible to decrease their undesirable outputs production provided their good output or, alternatively, by how much they are technologically capable of increasing their good output provided their level of bad output?
- Provided the countries or regions keep the same level of technological inefficiency with respect to the environment, what is the increase in the undesirable output production level that accompanies a 1% increase in the good output production?
- Do shadow prices of pollution witness about efficient global allocation of wealth and pollution?
- How different are the estimates of efficiencies and shadow prices obtained using parametric and nonparametric approaches and what are the errors of these estimates?

The cornerstone hypothesis of the work is that basic information about inputs and outputs of a set of economies can provide with the information on environmental efficiencies of these economies and shadow prices of environmental pollutants. Thus, the work has the following objectives:

- Set up a theoretical model that allow to estimate environmental efficiencies and shadow prices of pollutants on a country level as well as errors of these estimates
- Produce a computer code and make the estimations using it.
- Attempt to answer the research questions using the obtained estimates.
- Develop policy recommendations based on the results of the study.
- Prepare ground and propose the directions for further studies in the field.

The study has the following structure. We will estimate shadow prices and environmental efficiencies of economies (called hereafter as decision making units, DMUs) using parametric (*Translog* specification) and nonparametric (data envelopment analysis, DEA-based) approaches towards estimating output directional distance function. We will also estimate statistical characteristics of the

parametrically obtained estimates. Based on these characteristics as well as kernel estimated densities of the estimates, we will conclude on compatibility of these two approaches. In addition, we will draw conclusions and policy recommendations based on individual values of shadow prices of pollutants as well as inefficiencies of individual countries.

The rest of the work proceeds as follows. The second section provides literature review of the most important works related to the topic. The third section introduces a reader to the basic theory of sustainable development. The forth section builds up a basic economic model by providing economic intuition, while formalized mathematical model, which makes definitions and the assumptions used in the work as well as explains approach towards estimating the efficiencies and shadow prices is left for Appendix 1 (see Section Appendices). The fifth section develops a methodology of numerical estimation of environmental inefficiencies and shadow prices by parametric and nonparametric techniques and statistical characteristics of the obtained estimates. The sixth section introduces the data used in the empirical part of the study; presents the results of the estimation and provides discussion of the obtained results as well as three illustrative examples. The final section concludes and provides policy implications and further research recommendations.

2. LITERATURE REVIEW

All of the previous studies (at least among those we are aware of) on estimation of environmental efficiencies and shadow prices of pollution were considering separate plants within a single state's or country's industry (*e.g.*, pulp and paper plants in Michigan and Wisconsin, Dutch sugar-beet industry or electric power plants in Korea). Even these studies are by no means numerous. Therefore, our choice of the literature may be considered limited provided that (a) there are not many studies estimating environmental efficiencies of DMUs and shadow prices of pollutants, (b) there are no studies on estimating these for any DMUs related to CITs, and (c) there are no studies measuring these parameters on the macro level, *i.e.* considering countries as DMUs.

In order to structure the literature on the topic more efficiently we will first review literature taking alternative methodological approaches towards estimating shadow prices and inefficiencies and then we will see how the topic has been developing in general.

2.1. Approaches towards estimating efficiencies and shadow prices

It is important to make a note how shadow prices are usually estimated. A ratio of shadow prices of undesirable and desirable outputs (which is numerically equal to the slope of the technology set in a given point) can be estimated based on the Shephard-type distance functions[2] that give a dual representation of a technology. It is crucial to notice, however, that distance function measures efficiency

[2] Shephard (1970) proposed output distance function, which was later used as a basis for input distance function and directional distance functions.

of a DMU, while ratio of shadow prices measures marginal rate of technical substitution of a desirable output for undesirable. In other words, distance function and shadow price measure different things: the former indicates how far from the technological potential the DMU is, while the latter shows how much desirable output the DMU should forfeit if it wants to decrease pollution by one unit keeping the efficiency fixed, *i.e.* distance function measure long-run perspective of the economy, while shadow prices points on its short-run perspectives.

Two approaches are often observed in literature on estimating of shadow prices and distance functions. The first is parametric approach based on the methodology proposed by Aigner and Chu (1968) for estimating production function and then extended to cost functions (Pollak *et al*., 1984) and distance functions (Pittman, 1981; Pittman, 1983; Färe *et al*., 1993). The second is nonparametric, DEA-based approach.

Practically all studies before 2000 approached the problem of undesirable outputs production by using parametric specification of the distance functions (*e.g*., Färe *et al*., 1993; Coggins and Swinton, 1996; Chung *et al*., 1997; Färe *et al*., 2003). The main reason for this is that derivation of the shadow price involves differentiation of the distance function with respect to the outputs, which is more convenient in the case of parametric specification. DEA approach was used in the recent studies mostly, when determining shadow prices was not the purpose (Zaim and Taskin, 2000; De Koeijer *et al*., 2002). At the moment, only one study attempted to estimate shadow prices of pollution using nonparametric framework via DEA (Lee *et al*., 2002).

These two approaches usually provide similar but not the same results with respect to the absolute values of the efficiencies (Coelli and Perelman, 1999) in the case of only desirable outputs. The comparison is based on using assumption on the normal distribution of the estimates without estimating true statistical characteristics of them. Similar studies when some outputs are undesirable have not been done. It is also not studied if there is any qualitative difference in the obtained efficiency estimates (*i.e*., the DMU ranking with respect to efficiencies).

2.2. History of the studies in the field

Now, after we reviewed the literature that uses different approaches towards measuring environmental efficiencies and shadow prices of undesirable outputs, let us turn towards reviewing the progress in the area until now to develop an understanding of what is the investment of the current study in this field.

Although the earliest works on estimation of shadow prices of undesirable outputs (called 'bads' as an antonym to 'goods') were published in the beginning of 1980-s (Pittman, 1981; Pittman, 1983), such studies are not numerous, nevertheless provide theoretically well thought-out models suitable for such estimations.

These works of Pittman estimate shadow prices of pollutants of pulp and paper industry and give realistic figures pointing on inefficient distribution of resources in the industry. A decade later Färe *et al*. (1993) reviewed these results and pointed that the earlier studies were unable to determine the

shadow prices of the individual plants. For this reason, the authors use their previous theoretical work (Färe *et al*., 1989) on the use of nonparametric approach towards the efficiency analysis of the industries producing pollution in order to parametrically estimate shadow prices of individual pulp and paper plants of Michigan and Wisconsin.

Other works differ from the Färe's works mainly by the choice of the directional vector of the output distance function. Particularly, Färe *et al*. use the hyperbolic (Färe *et al*., 1989) and radial (Färe *et al*., 1993) efficiency rules; Boyd *et al*. (1996) use horizontal and vertical efficiency rules; Chambers *et al*. (1996) and Chung *et al*. (1997) make use of the general directional efficiency rule. Unfortunately, since the studies considered different object, it is hard to compare the results of these studies. However, it is possible to argue that in theory the choice of different directional vectors may give different values of the shadow prices of the individual objects as well as alters their relative efficiency (*i.e*. the objects having the same efficiency ranking according to one rule may have different efficiency rankings according to the other efficiency rule).

A recent study of the power plants in South Korea of Lee *et al*. (2002)[3] is notable among all other studies in the field. This paper proposes to estimate the shadow prices of pollution taking into account environmental inefficiency of production processes and pay attention to the theoretical validation of the efficiency rule. The study explicitly incorporates the weak efficiency assumption over the whole range of frontier in the output domain. The work bases its efficiency rule on the environmental protection plans of the plants.

Although such a method of choosing the directional vector may hardly be implemented (especially in transitional countries, where these plans are either difficult to access or do not exist at all), a consideration of environmental inefficiency of economies in estimation of the shadow prices is an important modification of Färe *et al*. (1993).

Another important innovation proposed by Lee *et al*. (2002) is its use of nonparametric specification of distance function in estimating shadow prices. This is a crucial breakthrough that allows comparing not only efficiency estimates from two approaches, but also shadow prices estimates.

2.3. Summary

From our review of the limited scope of the literature in the field we may conclude that there is a number of substantial niches exist, which we may attempt to fill by the current work:

No previous studies attempted to look on the countries as DMUs and, hence, estimate both their environmental efficiencies and shadow prices of undesirable outputs jointly.

Estimates of environmental efficiencies and shadow prices of undesirable outputs using different specifications (parametric and nonparametric) have not been compared yet.

Statistical characteristics (such as confidence intervals, standard errors, kernel density) of environmental efficiencies and shadow prices of undesirable outputs are not known for any of the specifi-

[3] For critique of theoretical development in the work of Lee *et al*. (2002), see Salnykov and Zelenyuk (2005*a*)

cations used (parametric and nonparametric). Estimating these characteristics would provide us more justified results while comparing them.

Many of the existing sustainability indicators are developed based on the biased *a priori* assumption on sustainability and aggregating unadjusted measures. An alternative indicator can be developed, which does not have these deficiencies.

2.4. Elements of sustainable development

It should be absolutely clear that before applying economic theory to environmental science issues, one should be familiarized with the basic aspects of environmental science, which are related to the study in order to understand how economic theory may address environmental issues.

Recent developments in environmental science resulted in a separation of a new field of sustainable development (Rao, 2000). Sustainable development (SD) is often considered a semi-philosophical concept that defines a utopian point of view on human development. The classical definition of SD was introduced in the famous Bruntland Report in 1987 and defines SD as the "…development that meets the needs of the present without compromising to the ability of future generations to meet their own needs" (WCED, 1987). Of course, such approach must seem utopian, since from economic perspective the term "meeting the needs" remains much room for speculation. In addition, it is hard to define the criteria of "compromising the ability of future generations to meet their own needs".

A comprehensive definition was proposed by Robert Costanza (1991). He proposes to define SD as

a relationship between dynamic human ecosystems and larger dynamic, but normally slower-changing ecological systems, in which:

a) human life can continue indefinitely,

b) human individuals can flourish,

c) human cultures can develop, but in which,

d) effects of human activities remain within bounds, so as not to destroy the diversity, complexity, and function of the ecological life support system.

Although this definition also is not absolutely clear from the economic perspective, *e.g*. the term 'flourishing' does not seem to be absolutely understandable, this definition provides with the basic idea what SD is mainly about. Sustainability involves three main components: economic sustainability (point *b* of Costanza's definition), social sustainability (point *c*) and environmental sustainability (point *d*). Therefore, it is appropriate to talk about three forms of capital SD involves: economic capital (man-made capital in the traditional economic sense); social capital (cultural heritage, morality, health, *etc*.); and environmental capital (natural and environmental resources).

Using idea of capital as a cornerstone of SD, two forms of sustainability are distinguished: weak and strong sustainability. Weak sustainability is usually defined as "a process of socioeconomic de-

velopment which is built on the sustainability approach, with an additional requirement that the worth of the capital stocks vector (valued at applicable shadow prices) is maintained constant, or undiminished, at each time interval, for ever" (Rao, 2000).

In other words, weak sustainability allows capital to transfer from one form to the other, *e.g*. from environmental to economic, while ensuring the total stock of capital is held undiminished. In contrast, strong form of sustainability constraints the total stock of each form of capital to stay undiminished, *i.e*. the transfer of environmental to economic capital is possible only in the case if an equivalent transfer is made back from economic to environmental capital. Corollary, we may consider development of a given economy weakly sustainable if the total of all desirable and undesirable outputs multiplied by the respective shadow prices is nonnegative. The development is strongly sustainable if the value of social expenditures on environment is not less than the total of all undesirable outputs multiplied by the respective shadow prices.

After discussing elements of sustainable development, we can conclude that the current study is important for sustainable development in many aspects including:

- Efficiency measure will provide with a distance of a given country to the best-practice frontier, *i.e*. a criterion to judge what is a potential of the country to increase its output without causing harm to the environment;
- Calculating total value of desirable and undesirable outputs produced by the DMU can provide with an additional sustainability indicator and basically may serve as a criterion for judging whether the DMU's development is sustainable or not;
- Estimates of shadow prices of environmental pollutants provide with marginal rates of substitution of desirable output for undesirable outputs;
- Corollary, we may able to forecast the growth in environmental pollution accompanied by a 1% growth of desirable output production within a given country *ceteris paribus*.

3. ELEMENTS OF PRODUCTION THEORY IN THE PRESENCE OF UNDESIRABLE OUTPUTS: INTUITIVE MODEL

Before discussing an intuitive model of production in the presence of undesirable output, we must introduce several simple, yet crucial, concepts.

3.1. Basic concepts of production theory

By *technology* here and below we mean a certain process that transforms a number of production factors or *inputs* into a number of products or *outputs*. The latter can be intended or *desirable*, such as many economic goods, *e.g*. guns, butter, *etc*. or unintended or *undesirable*, such as environmental damage, pollution, *etc*.

We will refer to *efficient production* throughout this work in the meaning of *technical efficiency*. Technical efficiency does not necessary imply revenue efficiency, cost efficiency or any other form of efficiency. In some sense, technical efficiency may be though as similar to Pareto-efficiency: the DMU is technically efficient or the input is used technically efficiently if it is not possible to produce more of any desirable output or less of any undesirable output without diminishing another desirable output or increasing another undesirable output given the DMU's input endowment.

We will refer to *feasible production* in the meaning of *technological feasibility*. Technological feasibility of certain input-output combination means that given the existing technologies it is possible to produce these outputs out of given inputs. Technological feasibility does not mean that the production is efficient.

3.2. Non-separable production of desirable and undesirable outputs

We start from observing economic activity of a number of DMUs. Each of the DMUs' economies produces desirable outputs (economic goods) and undesirable outputs (environmental pollution, degradation), which are produced jointly or *non-separably*. In the process of production the DMUs employ a number of inputs, such as labor, capital, land and energy.

Desirable outputs production in the closed DMU is usually aggregated in the form of GDP, which is a reliable estimate of what is produced within the geographical boundaries of a given country.

Undesirable outputs, however, are produced in a number of forms, which are not suitable for direct aggregation. This is one of the reasons why calculation of so called 'green GDP' is a disputable issue until now. 'Green GDP' is an indicator that attempts to measure the level of society's welfare by adjusting value of conventional GDP, *i.e.* an economic desirable output, by a total value of undesirable outputs, where the latter is a total of quantities of undesirable outputs weighted on their respective shadow prices (Hueting, 1991). At this, green GDP can be an indicator of a sustainability of the country's development: a positive value of it indicates that the value of economic output produced is bigger than a total value of the harm caused to the environment (*i.e.*, the development is weakly sustainable). The negative value points on weakly unsustainable development. Although the values of green GDP for individual countries are not estimated in this work, it is easy to do using our results and can be an interesting topic for the future studies in the field.

We assume that in the case of desirable outputs a society attempts to maximize total economic value of it, *i.e.* GDP. Therefore, we may imagine a DMU as a single production unit producing one desirable output and a number of undesirable outputs using production factors provided. For the sake of illustration, let us review a case of one input, one good and one bad output.

Desirable output production holding undesirable output production fixed. First, let us consider how change in input impacts desirable output production holding undesirable output fixed and provided input is used in the most efficient way. This is an ordinary case of conventional production function discussed in many economics textbooks (*e.g.*, Mas-Colell *et al.*, 1995) with some minor modifications. According to this concept, maximum possible desirable output increases as input in-

creases, but as input growth progresses, increase in desirable output becomes smaller (diminishing marginal product concept). Graphically, desirable output production function can be drawn as depicted on Fig. 1.

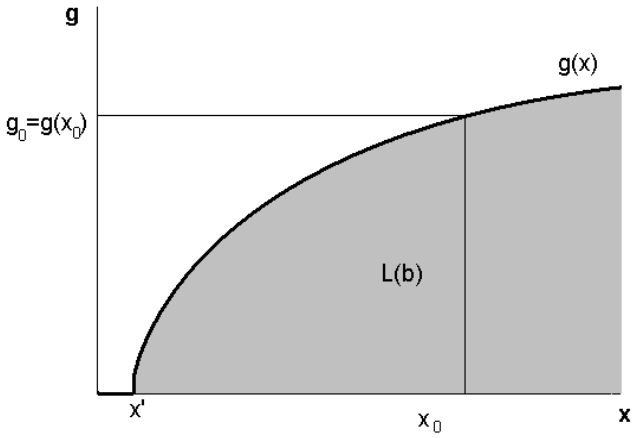

Fig. 1. Graphical representation of desirable output production

Here we plot dependence between input x and desirable output g keeping undesirable output fixed and assuming efficient use of input as a curve $g(x)$. It should be noted, however, that production of a desirable output can start only after the given level of undesirable output production is achieved (suppose it requires at least x' input). Before that input is used for production, simply no desirable output will be produced.

If we continue to keep undesirable output fixed but don't restrict production to efficient use of resources anymore (*i.e.*, a DMU can waste the input) then at any given input x_0 a DMU can produce desirable output at level less or equal than g_0, which corresponds to the most efficient use of x_0. Intuitively, if a DMU works efficiently, it produces as much as it technically capable to. If it does not work efficiently, it produces less than it could otherwise.

Similarly to conventional production theory, we introduce an *desirable output-input set*, $L(b)$, which is a set containing all technologically feasible combinations of desirable output and input holding undesirable output fixed, *i.e.* a set containing combinations of input and desirable output such as this level of input can produce this level of desirable output and the level of undesirable output set exogenously at level b. Graphical illustration of undesirable output set is given on Fig. 1 as a shaded area. It should be understood in the following way: once we set undesirable output production on the fixed level, we plot all technologically feasible combinations of input and desirable output with different levels of efficiency. The resulting area is desirable output-input set.

Undesirable output production holding desirable output production fixed. Similarly, we can elaborate on production of undesirable output. Since undesirable outputs are similar to desirable outputs in the sense that they are also physical outputs. The following discussion of production of undesirable outputs is based on Fig. 2.

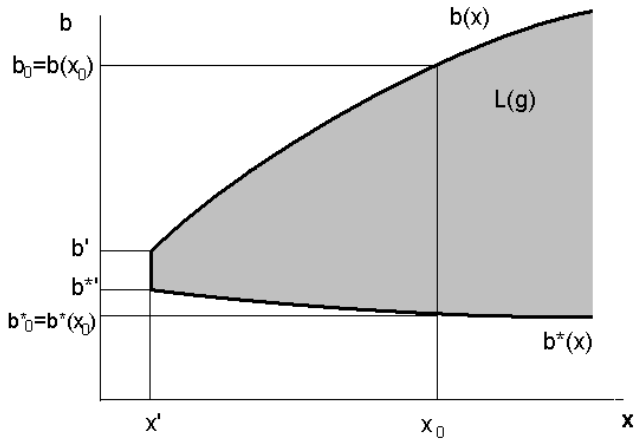

Fig. 2. Graphical representation of undesirable output production

Given the level of the desirable output production, production of undesirable output can start only after at least b' of undesirable output is produced, or if a DMU uses the pollution abatement technologies, after at least $b^{*'}$ is produced. These levels of desirable and undesirable outputs require investment of x' of input. If we start increasing output (keeping desirable output production constant), undesirable output level will change along the path $b(x)$ if no pollution-abatement technologies are used, $b^*(x) \leq b^{*'}$ if all possible pollution-abatement technologies are used, or any level between these two values depending on the level of execution of pollution-abatement technologies. We will distinguish between $b(x)$ and $b^*(x)$ by calling them undesirable output production function and abated undesirable output production function respectively. At this, we agree to consider $b^*(x)$ technologically efficient, while $b(x)$ technologically inefficient.

Therefore, at any given level of input $x_0 > x'$ we may expect a DMU to produce $b^*(x_0)$ of undesirable output if it is functioning in the most efficient way, $b_0 = b(x_0)$ if it is functioning in the most inefficient way or any level in between these two assuming that production of the desirable output remains constant. Corollary, we will call the set containing all technologically feasible combinations of undesirable output and input required to produce it given that desirable output level is held constant *undesirable output-input set*, which is depicted by shaded area on the picture and denoted by $L(g)$. It should be understood in the following way: once we set desirable output production on the fixed level, we plot all technologically feasible combinations of input and undesirable output with different levels of efficiency. The resulting area is desirable output-input set.

Joint desirable output — undesirable output production holding input fixed. Finally, we consider the relationship between undesirable and desirable output production levels holding input fixed. This relationship is illustrated on Fig. 3.

Provided an input level, a DMU can decide on how much of each outputs it wants to produce. At this, if it decides to produce less than some critical amount of undesirable output b', no desirable output can be produced. Intuitively it should be understood in the following way: if a DMU wants to produce something, it should first experience some environmental damage prior any production

takes place. These damages may include heating up machinery (and producing air pollution), constructing facility (and damaging land and creating fragmentation of habitats), *etc*. They are non-productive (in terms of desirable output), but required to enable any desirable output production. We agree to call this critical amount as a *minimum technically efficient undesirable output*. On the other hand, physical laws restrict total undesirable output production to a limited number *b*" (in other words, given 1 kilogram of fuel it is impossible to produce more than 1 kilogram of pollution). We will call such level *maximum possible undesirable output*.

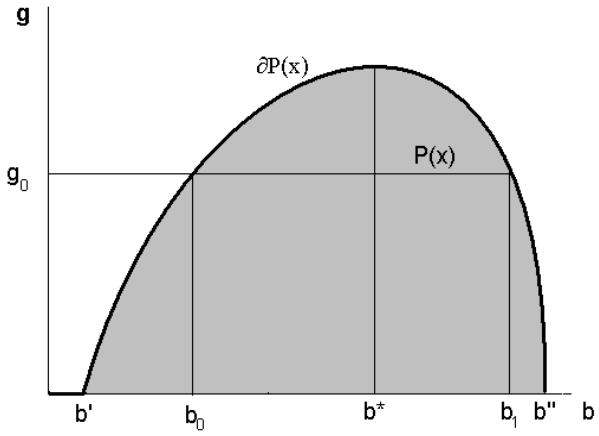

Fig. 3. Graphical representation of joint desirable-undesirable output production

If a DMU decides to produce an amount of desirable output equal to g_0, its choice of undesirable output production is restricted to a minimum of b_0 (the most efficient point) to a maximum b_1 (the least efficient point). We agree to call all technologically feasible combinations of desirable and undesirable outputs given the level of input *output set*. This set is depicted by the shaded area and should be understood in the following way: once we set input on the fixed level, we plot all technologically feasible combinations of desirable and undesirable outputs with different levels of efficiency. The resulting area is output set.

An important value of the output set is that it allows an explicitly focus on substitutability between desirable and undesirable outputs and study them holding inputs fixed. That is especially crucial as we observe that many of the inputs (labor, land) can be considered as given exogenously.

The solid line on the drawing represents the maximum possible desirable output, which can be produced given the input and the level of undesirable output. However, not all these points are favorable for a DMU. The points to the right of the point b^* have the respective points to the left of b^*, which provide the same level of desirable output, but smaller level of undesirable output (*e.g*., consider the pair $b_0 - b_1$). Therefore, left part of the solid part is more favorable to the DMUs in terms of efficiency (excluding its horizontal portion). We agree to call this part of the line as *production possibility frontier* (*PPF*) and denote it by $\partial P(\mathbf{x})$, while b^* is agreed t be accepted as the *maximum technologically efficient undesirable output*.

Joint production of outputs at different input levels. We summarize our discussion of production process in the presence of undesirable outputs by constructing a *technology set*. It is defined as all possible combinations of inputs, desirable and undesirable outputs that are technically feasible. General shape of technology set in the case of one input, one desirable and one undesirable output is depicted on Fig. 4.

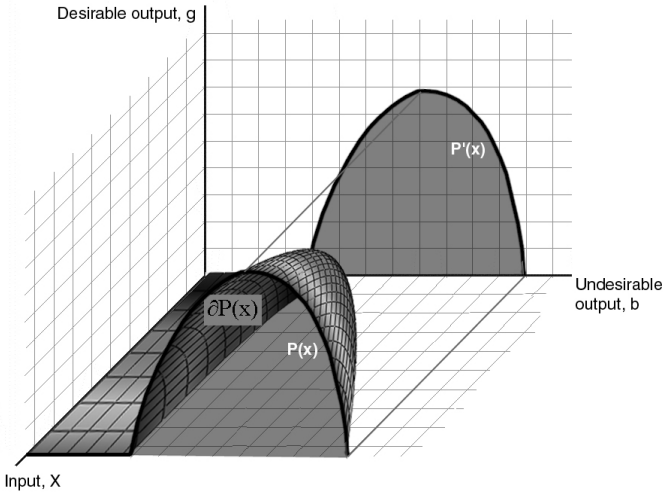

Fig. 4. Graphical representation of technology set

This three-dimensional picture provides with a pretty good idea of what input-output combinations are feasible. We agree to call the set containing all technologically feasible combinations *technology set*. In one input-one desirable-one undesirable output case it will have a shape as depicted on the diagram. The technology set will include the convex hull (including points inside the shell) and the surface on the left of the hull. The intuition of including this surface in the technology set is absolutely the same as including horizontal portion on the lest of P(**x**) discussed in the previous section.

The left portion of the hull surface represents technologically efficient combinations of inputs and outputs and has the same intuition as PPF in the previous section.

When we know the input endowment we posses, we can cut a slice of the technology set at the given input level. The resulting area corresponds to the output set discussed before.

3.3. Environmental efficiency

Let us return to the choice of DMU once it decides to produce g_0. Since b is undesirable, a DMU would want to produce as little of it as possible, *i.e.* b_0. However, this is not always the case. In practice, some DMUs decide to produce more than this amount, *i.e.* to be inefficient. Therefore, the important question is: why a DMU would decide to be inefficient and produce more pollution than it could otherwise? An answer to this question is: this happens either due to the market failures or due to a profit-maximizing behavior. The first option involves asymmetric information, where a

DMU does not know that it could produce less of pollution. The second option involves a conclusion of a DMU that it is too expensive to be efficient in the sense that efficient technologies it has an access to are too expensive to justify a decrease in the pollution.

Now, we present a measure of a DMU's efficiency. For this purpose we propose to use *Shephard-type directional output distance function*. An intuition of the former can be understood from Fig. 5.

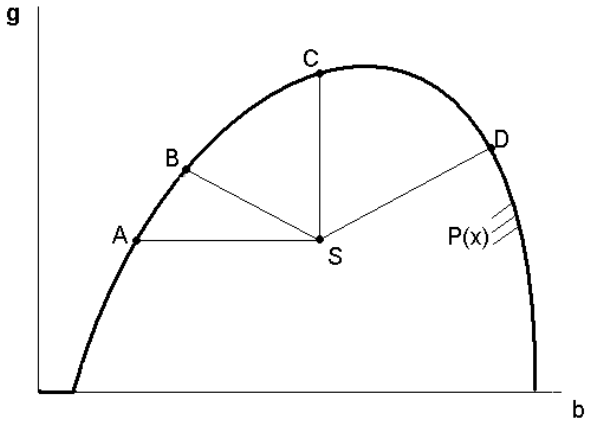

Fig. 5. Graphical illustration of efficiency measure using ODDF: horizontal (A), general (B), vertical (C) and radial (D) direction

We start from observing a DMU producing an inefficient combination of outputs (point S). We accept distance of this point to $\partial P(\mathbf{x})$ in a given direction as a measure of efficiency. If this distance is equal to zero, the observation is fully efficient. It should be noted that this direction is set by ourselves and has roots in our understanding of how a DMU should behave in its attempt to become more efficient. Suppose, we believe that an efficiency increase must imply decrease in undesirable output preserving desirable output on the constant level. It means that we restrict movement of the DMU towards the efficient point to *horizontal* direction represented by the line SA on the drawing. Similarly, we may believe that an increase in efficiency must be accompanied with a growth of desirable output while holding an undesirable output constant. By this, we set a *vertical* direction represented by a line SC on the drawing. Finally, we may think that a DMU must increase its desirable and decrease its undesirable outputs if it wants to become more efficient. By thinking so, we set a *general* direction represented by the line SB on the drawing. All these directions project an observation to an efficient position A, B or C. At this, distances SA, SB and SC will represent the efficiency measures, which depend on our belief of the DMUs 'optimal' behavior.

It must be acknowledged, however, that some previous studies (*i.e.*, Färe *et al.*, 1993) attempted to employ *radial* direction by assuming that a DMU should increase both desirable and undesirable output in its attempt to become more efficient (radial direction SD). However, such approach will lead us to a point D, which is inefficient according to our understanding of efficiency as it was discussed above).

An important question related to measuring efficiency is: what direction is the best proxy of the DMUs 'optimal' behavior. We expect that a typical society will tend to both increase desirable and decrease undesirable output in their attempts of being more efficient, and, hence, follow general direction.

We agree to call the principle according to which the society changes its outputs while becoming more efficient as *efficiency rule* (ER). Here and below we distinguish horizontal ER, vertical ER and general ER as those based on the respective directions.

In the empirical part of the work we focus on the latter efficiency rule. This is mostly due to the fact that the directional function with this efficiency rule was demonstrated to have some nice properties: (i) it is the first order approximation of the hyperbolic efficiency measure and (ii) it can be viewed as a counterpart of the Shephard's output distance function when some outputs are undesirable. The issue of the choice of the efficiency rule will be discussed more closely in the mathematical model in Appendix.

3.4. Shadow prices

Our final section in the intuitional framework is devoted towards explaining the intuition of the shadow prices and the theoretical way to approach their measurement.

Shadow prices of undesirable outputs can be considered as a cornerstone in the environmental accounting. Hueting (1991) acknowledged that impossibility to measure shadow prices of environmental pollution disables many important achievements in the field, such as correction of national income for environmental degradation, constructing environmental demand curve and setting an efficient environmental taxation.

Shadow prices of environmental resources are often understood as (Rao, 2000):

> *the "true" worth of a resource …* [*they*] *are related to the specification of objectives, derived from the general socioeconomic philosophy … these prices are designed to reflect the opportunity cost and, thus, the real worth of a resource.*

This intuition allows us to consider shadow prices of pollution as *the internal valuation of environmental degradation* (*connected to each pollutant*) *by a given society*. This concept is closely related to the society's utility function and the respective mathematical demonstrations will be provided in the following section.

Since there is no market for environmental pollution, it is not possible to observe shadow prices of the pollutants. For this reason, a number of approaches to evaluate environmental resources have been developed. These include contingent valuation method, travel cost method, hedonic price methods, *etc*. Most of these methods involve sociological or market analyses, which are subject to serious drawbacks related to representativeness of the sample, limited choice of pollutants and aggregation issues.

In order to propose an alternative method of measuring shadow prices, we may start from recalling a well-known economic fact that according to the rationality assumption a rational revenue-

maximizing DMU will be always located at the point on PPF, where the slope of the latter is equal to the ratio of the prices of the outputs. Fig. 6 represents measure of shadow price in one desirable — one undesirable output case.

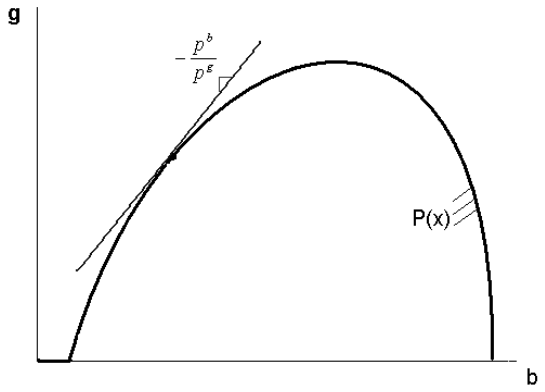

Fig. 6. Measure of shadow price of undesirable output

The slope of the PPF in the point of observation equals the negative ratio of the shadow price of pollutant to the shadow price of desirable output. We agree to call this ratio *normalized shadow price* of undesirable output. Minus in front of the ratio points on negative shadow price of the undesirable output, which is understandable, since people are willing to pay to get rid of it, not to get more of it as in the case with desirable outputs. If we assume that shadow price of desirable output equals its market price, we can neglect the denominator and obtain absolute shadow price of undesirable output.

An important interpretation of the normalized shadow price of an undesirable output is: normalized shadow price of a bad shows how much of a good output should be foregone in order to decrease bad output by one unit provided the efficiency remains the same. Alternatively, it shows the increase of a bad output should good output increase by one unit and efficiency stays the same. A valuable application of this interpretation is that it allows seeing the environmental outcomes (in terms of increasing pollution) of economic growth (in terms of growing output). For example, we may estimate if a country can meet its Kyoto protocol targets given its economic targets and estimated environmental inefficiency.

It has been demonstrated that once we estimated an efficiency measure, we can derive a normalized shadow price out of this estimate. This method of shadow prices estimation is clearly superior to the aforementioned methods of environmental valuation, since it estimates the slope of PPF rather than relies on subjective questionnaires or market studies. Moreover, it should be possible to estimate statistical characteristics of the shadow prices estimates, while in the case of environmental valuation methods it is hardly possible.

The intuitive model is presented formally with the list of definitions and assumptions in Appendix 1 (see Section Appendices).

4. METHODOLOGY OF THE EMPIRICAL ESTIMATION

In this section we will present methodology to estimate ODDF with general DV and shadow prices of undesirable outputs as well as methods of statistical analysis for them. The section will also comment the data to be used as well as issues in forming the sample.

Estimation of the ODDF and the shadow prices can be realized by using various techniques. The traditional studies in the field follow Aigner and Chu (1968), Schmidt (1978) and Greene (1980) in specifying a parametric form of technology and solve for the parameters using the linear programming.

4.1. Estimating ODDF: parametric approach

Chung (1996)[4] proposed to parameterize ODDF by the Translog function for a general DV. This specification is flexible, linear in coefficients and provides second order approximation for any technology. In addition, it does not suggest strong disposability of outputs, which is important when undesirable outputs are under review. Chung defines Translog specification of ODDF (adjusted for the purposes of the current study, where L=1) as

$$\begin{aligned}\ln\left[1+\vec{D}_0(\mathbf{x},\mathbf{g},\mathbf{b}|\mathbf{g},\mathbf{b})\right] = {} & \alpha_0+\alpha_1\ln g+\sum_m\beta_m\ln b_m+\sum_n\gamma_n\ln x_n \\ & +\frac{1}{2}\alpha_{11}(\ln g)(\ln g)+\frac{1}{2}\sum_m\sum_{m'}\beta_{mm'}(\ln b_m)(\ln b_{m'}) \\ & +\frac{1}{2}\sum_n\sum_{n'}\gamma_{nn'}(\ln x_n)(\ln x_{n'})+\frac{1}{2}\sum_n\delta_n(\ln g)(\ln x_n) \\ & +\frac{1}{2}\sum_m\sum_n\varepsilon_{mn}(\ln b_m)(\ln x_n)+\frac{1}{2}\sum_m\zeta_m(\ln g)(\ln b_m),\end{aligned} \tag{1}$$

where Greek letter are the parameters we solve for.

The reason for having $\ln\left[1+\vec{D}_0(\cdot)\right]$ instead of $\ln\left[\vec{D}_0(\cdot)\right]$ is that domain of the logarithmic function is positive numbers, while $\vec{D}_0(\cdot)$ can take a zero value on ∂P(**x**). Therefore, we have to make an artificial restriction of the domain of the function to the positive numbers only.

Chung (1996) then estimates the parameters of (1) by minimizing the sum of the deviations of the observations from the efficient level, *i.e.* ∂P(**x**). Mathematically, the optimization problem is

$$\begin{aligned}&\min\sum_k\left[\ln\left(1+\vec{D}_0(\cdot)\right)-\ln\left(1+\vec{D}_0(\cdot)\big|_{\partial P(\mathbf{x})}\right)\right] \\ &\equiv\min\sum_k\left[\ln\left(1+\vec{D}_0(\cdot)\right)-\ln(1+0)\right]\equiv\min\sum_k\left[\ln\left(1+\vec{D}_0(\cdot)\right)\right].\end{aligned} \tag{2}$$

[4] Similar approach was used by Hailu and Veeman (1998) to estimate input distance function (IDF) and by Färe *et al.* (1993) to estimate ODF.

Then (1) can be estimated by using (2) as an objective function as

$$\min \sum_k \left[\ln\left(1+\vec{D}_0(\mathbf{x}^k,\mathbf{g}^k,\mathbf{b}^k \,|\, \mathbf{g}^k,\mathbf{b}^k)\right)\right], \tag{3}$$

s.t.

(i) $$\ln\left(1+\vec{D}_0(\mathbf{x}^k,\mathbf{g}^k,\mathbf{b}^k \,|\, \mathbf{g}^k,\mathbf{b}^k)\right) \geq 0, \qquad k=1,...,K,$$

(ii)
$$\frac{\partial\left[n(1+\vec{D}_0(.)\right]}{\partial(\ln g)} \leq 0,$$
$$\frac{\partial\left[n(1+\vec{D}_0(.)\right]}{\partial(\ln b_m)}, \qquad m=1,...,M,$$

(iii)
$$\alpha_1 - \sum_m \beta_m = -1,$$
$$\alpha_{11} - \sum_m \zeta_m = 0, \qquad m, m' = 1,...,M,$$
$$\zeta_m - \sum_{m'} \beta_{mm'} = 0, \qquad n=1,...,N,$$
$$\delta_n - \sum_m \varepsilon_{mn} = 0,$$

(iv) $$\beta_{mm'} = \beta_{m'm}, \qquad \gamma_{nn'} = \gamma_{n'n}.$$

Constraint (i) corresponds to Axiom 13 requiring that all observations are technologically feasible as all observations in the technology set have $\vec{D}_0(\cdot) \geq 0$. (ii) guarantees nonnegative shadow prices for good outputs and nonpositive shadow prices for bad outputs. (iii) imposes functional properties of the ODDF as an approximation of the hyperbolic efficiency measure. Finally, (iv) imposes symmetry on Hessian according to the Young's theorem.

Hence, we need to minimize a single objective function subject to a total of

$$K(M+2) + 0.5(M(M+1) + N(N+1)) + 2$$

constraints. The optimization results a set of $3 + 2M + 2N + M^2 + MN + N^2$ estimated parameters of (1). We agree to denote this set of estimates $\hat{\theta}(\mathbf{g},\mathbf{B},\mathbf{X})$, where $\mathbf{B} = (\mathbf{b}_1 \ \mathbf{b}_2 \ \ldots \mathbf{b}_M) \in \Re_+^K \times \Re_+^M$ and $\mathbf{X} = (\mathbf{x}_1 \ \mathbf{x}_2 \ \ldots \mathbf{x}_N) \in \Re_+^K \times \Re_+^N$ are matrices containing observed values of undesirable outputs and inputs for all DMUs. $\hat{\theta}(\mathbf{g},\mathbf{B},\mathbf{X})$ is an estimate of the true set of parameters of (1) θ. Plugging into (1) $\hat{\theta}(\mathbf{g},\mathbf{B},\mathbf{X})$ and the observations for a given DMU will result an estimated ODDF value for that DMU in $\ln\left[1+\hat{\vec{D}}_O(\cdot)\right]$ terms. A transformation of it as

$$\hat{\vec{D}}_0\left(\mathbf{x}^k,\mathbf{g}^k,\mathbf{b}^k \,|\, \mathbf{g}^k,\mathbf{b}^k\right) = \exp\left\{\ln\left[1+\hat{\vec{D}}_0\left(\mathbf{x}^k,\mathbf{g}^k,\mathbf{b}^k \,|\, \mathbf{g}^k,\mathbf{b}^k\right)\right]\right\} - 1, \quad \forall k = 1,...,K \tag{4}$$

will supply $\hat{\vec{D}}_0\left(\mathbf{x}^k,\mathbf{g}^k,\mathbf{b}^k\middle|\mathbf{g}^k,\mathbf{b}^k\right)$, an estimated value of the true ODDF $\vec{D}_0\left(\mathbf{x}^k,\mathbf{g}^k,\mathbf{b}^k\middle|\mathbf{g}^k,\mathbf{b}^k\right)$ for a given DMU. We agree to denote this estimate as $\hat{\tau}^k\left(g^k,\mathbf{b}^k,\mathbf{x}^k\middle|\hat{\theta}(\mathbf{g},\mathbf{B},\mathbf{X})\right)$ and the true ODDF value as $\tau^k\left(g^k,\mathbf{b}^k,\mathbf{x}^k\middle|\theta\right)$.

4.2. Estimating shadow prices: parametric approach

The shadow prices are estimated in line with as

$$\hat{p}_m{}^b = p^g \frac{\partial\hat{\vec{D}}_0(\cdot)/\partial b_m}{\partial\hat{\vec{D}}_0(\cdot)/\partial g}, \tag{5}$$

where $\hat{\vec{D}}_0(\cdot)$ is a short notation for $\hat{\vec{D}}_0\left(\mathbf{x},\mathbf{g},\mathbf{b}|\mathbf{g},\mathbf{b}\right)$. At this,

$$\frac{\partial\hat{\vec{D}}_0(\cdot)}{\partial b_m} = \frac{\partial\hat{\vec{D}}_0(\cdot)}{\partial\ln\left[1+\hat{\vec{D}}_0(\cdot)\right]}\cdot\frac{\partial\ln\left[1+\hat{\vec{D}}_0(\cdot)\right]}{\partial(\ln b_m)}\cdot\frac{\partial(\ln b_m)}{\partial b_m}, \tag{6}$$

and

$$\frac{\partial\hat{\vec{D}}_0(\cdot)}{\partial g} = \frac{\partial\hat{\vec{D}}_0(\cdot)}{\partial\ln\left[1+\hat{\vec{D}}_0(\cdot)\right]}\cdot\frac{\partial\ln\left[1+\hat{\vec{D}}_0(\cdot)\right]}{\partial(\ln g)}\cdot\frac{\partial(\ln g)}{\partial g}. \tag{7}$$

Hence (5) can be rewritten as,

$$\hat{p}_m{}^b = p^g \frac{\dfrac{\partial\hat{\vec{D}}_0(\cdot)}{\partial\ln\left[1+\hat{\vec{D}}_0(\cdot)\right]}\cdot\dfrac{\partial\ln\left[1+\hat{\vec{D}}_0(\cdot)\right]}{\partial(\ln b_m)}\cdot\dfrac{\partial(\ln b_m)}{\partial b_m}}{\dfrac{\partial\hat{\vec{D}}_0(\cdot)}{\partial\ln\left[1+\hat{\vec{D}}_0(\cdot)\right]}\cdot\dfrac{\partial\ln\left[1+\hat{\vec{D}}_0(\cdot)\right]}{\partial(\ln g)}\cdot\dfrac{\partial(\ln g)}{\partial g}} = \tag{8}$$

$$= p^g \frac{\partial\ln\left[1+\hat{\vec{D}}_0(\cdot)\right]\Big/\partial(\ln b_m)}{\partial\ln\left[1+\hat{\vec{D}}_0(\cdot)\right]\Big/\partial(\ln g)}\cdot\frac{g}{b_m}.$$

Some simple algebra allows to derive from (4) that

$$\frac{\partial\ln\left[1+\hat{\vec{D}}_0(\cdot)\right]}{\partial(\ln b_j)} = \hat{\beta}_j + \sum_m\hat{\beta}_{mj}(\ln b_m) + \frac{1}{2}\sum_n\hat{\varepsilon}_{jn}(\ln x_n) + \frac{1}{2}\hat{\zeta}_j(\ln g), \tag{9}$$

$$\frac{\partial\ln\left[1+\hat{\vec{D}}_0(\cdot)\right]}{\partial(\ln g)} = \hat{\alpha}_1 + \hat{\alpha}_{11}(\ln g) + \frac{1}{2}\sum_n\hat{\delta}_n(\ln x_n) + \frac{1}{2}\sum_m\hat{\zeta}_m(\ln b_m). \tag{10}$$

Corollary, based on Axiom 12, (8), (9) and (10) shadow price of *j*-th undesirable output for *k*-th DMU can be numerically estimated as

$$\hat{p}_m^{\,bk} = \frac{\hat{\beta}_j + \sum_m \hat{\beta}_{mj}(\ln b_m^{\,k}) + \frac{1}{2}\sum_n \hat{\varepsilon}_{jn}(\ln x_n^{\,k}) + \frac{1}{2}\hat{\zeta}_j(\ln g^k)}{\hat{\alpha}_1 + \hat{\alpha}_{11}\left(\ln g^k\right) + \frac{1}{2}\sum_n \hat{\delta}_n(\ln x_n^{\,k}) + \frac{1}{2}\sum_m \hat{\zeta}_m(\ln b_m^{\,k})} \cdot \frac{g^k}{b_m^{\,k}}, \tag{11}$$

which are estimates of the true value of shadow prices p_m^{bk}.

4.3. Estimating ODDF: nonparametric approach

In the most recent works (*e.g.*, Lee *et al*., 2002), the estimation of ODDF is realized using non-parametric production modeling.

First, we introduce the model developed by Lee and his co-authors and then we present some modifications to it, which are based on our set of axioms.

Piecewise-linear production technology is described by Lee *et al*. as

$$P(\mathbf{x}) = \{(g, b): g \le \mathbf{V}\mathbf{z},\ b \ge \mathbf{W}\mathbf{z},\ \mathrm{X}\mathbf{z} \leqq \mathbf{x},\ \mathbf{e}^T\mathbf{z} \le 1,\ \mathbf{z} \in \Re_+^{\,K}\}, \tag{12}$$

where $\mathbf{V} \in \Re_+^{\,K}$ is a row vector consisting of the observed good output values; $\mathbf{W} \in \Re_+^{\,K}$ is a row vector of the observed bad output values; $\mathrm{X} \in \Re_+^{\,N} \times \Re_+^{\,K}$ is a matrix of the observed inputs; $\mathbf{e}^T$ is a row vector consisting of ones; $\mathbf{z} \in \Re_+^{\,K}$ is a column vector representing intensity variables, *i.e.* the variables used to weight different DMUs in constructing the reference frontier, which estimates P(**x**).

Let **d** = (α, β) then $\vec{D}_0(\cdot)$ for *k*-th economy can be calculated based on a given production technology by solving the following linear programming problem

$$\max \tau^k \ , \tag{13}$$

s.t.

(i) $$\mathbf{V}\mathbf{z} \ge (1 + \alpha\tau^k)g^k \qquad k = 1, \ldots, K,$$

(ii) $$\mathbf{W}\mathbf{z} \le (1 + \beta\tau^k)b^k,$$

(iii) $$X\mathbf{z} \ \leqq \ \mathbf{x}^k,$$

(iv) $$\mathbf{e}^T\mathbf{z} \le 1,$$

(v) $$\mathbf{z} \geqq \mathbf{0}_K, \ \tau^k \ge 0.$$

In contrast to Lee *et al*., we estimate true output set with

$$\hat{\mathrm{P}}\,(\mathbf{x}|\mathrm{HBOM}) = \{(g, \mathbf{b}): g \le \mathbf{g}\mathbf{z},\ \mathbf{b} \geqq \mathbf{B}\mathbf{z},\ \mathbf{X}\mathbf{z} \leqq \mathbf{x},\ \mathbf{e}^T\mathbf{z} \le 1,\ \mathbf{z} \in \Re_+^{\,K}\}, \tag{14}$$

under NIRS assumption (which is in line with Lee's assumption on the returns to scale) and

$$\hat{P}(\mathbf{x}|MOM)=\{(g, \mathbf{b}): g\leq \mathbf{gz}, \mathbf{b}\geqq \mathbf{Bz}, \mathbf{Xz}\leqq \mathbf{x}, \mathbf{e}^T\mathbf{z}=1, \mathbf{z}\in \Re_+^K\}, \quad (15)$$

in the VRS[5] case (which is based on Axiom 5).

In (14) and (15) $\mathbf{e}^T$ is a row vector consisting of ones; $\mathbf{z}\in \Re_+^K$ is a column vector representing intensity variables.

ODDF for a *k*-th DMU using our chosen DV will be estimated through

$$\max \tau^k, \quad (16)$$

s.t.

(i) $$\mathbf{Gz} \geq (1+\tau^k)g^k, \qquad k=1,...,K,$$

(ii) $$B\mathbf{z} \leqq (1-\tau^k)\mathbf{b}^k,$$

(iii) $$X\mathbf{z} \leqq \mathbf{x}^k,$$

(iv) $$\mathbf{e}^T\mathbf{z} \leq 1,$$

(v) $$\mathbf{z} \geqq 0_K, \quad \tau^k \geq 0$$

in the NIRS case and

$$\max \tau^k \quad (17)$$

s.t.

(i) $$\mathbf{Gz} \geq (1+\tau^k)g^k, \qquad k=1,...,K,$$

(ii) $$B\mathbf{z} \leqq (1-\tau^k)\mathbf{b}^k,$$

(iii) $$X\mathbf{z} \leqq \mathbf{x}^k,$$

(iv) $$\mathbf{e}^T\mathbf{z} = 1,$$

(v) $$\mathbf{z} \geqq 0_K, \quad \tau^k \geq 0$$

in the VRS case.

Each of the two cases is a set of K problems of linear maximization over $K+1$ parameter subject to $3 + M + N + K$ linear inequality constraints (in the NIRS case) or $2 + M + N + K$ linear inequality and 1 equality constraint (in the VRS case).

[5] DEA estimation under VRS assumption allows wrapping all observations in the smallest possible convex free disposable hull. In such a way, we may allow for good output production start only after a certain threshold in a bad production is achieved.

4.4. Estimating shadow prices: nonparametric approach

Having estimated the ODDF values, we may calculate the values of the shadow prices on the production possibility frontier and out of it. We discuss an exact procedure of doing it using (17) as an example, but the same pattern can be used to (16) as well.

The first thing we should do is to find projections of all observations on ∂P(**x**) according to the DV chosen. This point will have the following respective coordinates

$$g^{e^k} = \left(1 + \hat{\vec{D}}_O^k(\cdot)\right) g^k \tag{18}$$

and

$$\mathbf{b}^{e^k} = \left(1 - \hat{\vec{D}}_O^k(\cdot)\right) \mathbf{b}^k, \tag{19}$$

where by $\hat{\vec{D}}_O^k(\cdot)$ is a short notation for $\hat{\vec{D}}_O\left(\mathbf{x}^k, \mathbf{g}^k, \mathbf{b}^k \middle| \mathbf{g}^k, \mathbf{b}^k\right)$.

At this, all points will be taken to the estimated ∂P(**x**).

Next, we run K linear programming tasks for each DMU $k = 1, ..., K$ on the 'adjusted' data

$$\max_{\mathbf{z},\, \tau^k} \tau^k \tag{20}$$

s.t.

(i) $$\mathbf{G}\mathbf{z} \geq (1+\tau^k) g^{ek}, \qquad k = 1, ..., K,$$

(ii) $$B\mathbf{z} \leqq (1-\tau^k)\mathbf{b}^{ek},$$

(iii) $$X\mathbf{z} \leqq \mathbf{x}^k,$$

(iv) $$\mathbf{e}^T \mathbf{z} = 1,$$

(v) $$\mathbf{z} \geqq 0_K, \quad \tau^k \geq 0.$$

We obtain a set of new optimal values of τ and **z** as well as a set of Lagrange multipliers for each constraint in (20). The Lagrange multipliers to (i) and (ii) in (20) are equal the shadow prices of constraints in the conventional mathematical-programming sense. They are also the normalized shadow prices in the conventional economic sense. Ratios of the respective Lagrange multipliers are equal to the ratios of $\partial \vec{D}_O^k(\cdot)/\partial g^k$ and $\partial \vec{D}_O^k(\cdot)/\partial b_m^k$ ($m = 1, ..., M$, $k = 1, ..., K$) respectively. We calculate estimates of the shadow prices for a DMU as

$$\hat{p}_m^{b\,k} = p^{g\,k} \frac{\lambda_{(ii)m}^k}{\lambda_{(i)}^k} = p^{g\,k} \frac{\lambda_{(ii)m}^k}{\lambda_{(i)}^k} \frac{1 - \hat{\vec{D}}_O^k(\cdot)}{1 + \hat{\vec{D}}_O^k(\cdot)}, \tag{21}$$

where $\lambda_{(i)}^k$ is a Lagrange multiplier for a k-th DMU's constraint (i) in (20), $\lambda_{(ii)m}^k$ is a Lagrange multiplier for a k-th DMU's constraint (ii) for a polluter m.

It must be noted however, that nonparametric approach may provide nonunique estimated values of shadow prices (since (20) may have nonunique solution and, hence, nonunique Lagrange multipliers to each constraint). It is not clear at the moment how to solve the problem of nonuniqueness of estimates and identify a range of estimated values. For that reason, nonparametric approach in estimating shadow prices seems to be less reliable than parametric.

4.5. Evaluating statistical characteristics of estimates: bootstrap technique

We estimate statistical characteristics of the parametrically obtained estimates by adapting a smooth homogeneous bootstrap originally proposed for DEA-estimated efficieincies by Simar and Wilson (1998). We run $Q = 5000$ iterations to obtain bootstrap estimates of (1) $\hat{\theta}_q^*, q = 1, ..., Q$ using the smoothing module that employs kernel estimated densities of ODDF. Plugging $\hat{\theta}_q^*$ and the respective observations into (4) and (11) results bootstrap estimates of ODDF and shadow prices $\hat{\tau}^{*k}_q$ and $\hat{p}^{*\,bk}_{m\;q}$. We do not employ bootstrap on nonparametric estimates as the size of the sample is too small for it relative to dimensionality of the problem.

The general algorithm of the smooth bootstrap technique employed can be summarized as follows.

Let

$$\mathbf{g} = \left(g^1, ..., g^K\right)^T \in \Re_+^K,$$

$$\mathbf{B} = \left(\mathbf{b}_1, ..., \mathbf{b}_M\right) \in \Re_+^K \times \Re_+^M \text{ and}$$

$$\mathbf{X} = \left(\mathbf{x}_1, ..., \mathbf{x}_N\right) \in \Re_+^K \times \Re_+^N$$

be the observed matrices of desirable and undesirable outputs and inputs for *K* DMUs.

Using (3) and observations, obtain estimated values of parameters of (1), $\hat{\theta}(\mathbf{g}, \mathbf{B}, \mathbf{X})$. Using (4) calculate $\hat{\tau} = \left\{\hat{\tau}^1, ..., \hat{\tau}^K\right\}$ $\hat{\tau}^k\left(g^k, \mathbf{b}^k, \mathbf{x}^k \middle| \hat{\theta}(\mathbf{g}, \mathbf{B}, \mathbf{X})\right)$, $\forall k = 1, ..., K$.

Using kernel density estimator and reflection method calculate bandwidth of kernel estimated distribution of estimated ODDF $\hat{\tau} \sim \hat{f}(\hat{\tau})$ as, for example,

$$h = 1.06 \cdot \min\left\{\sigma_{\mathrm{T}}, iqr(\mathrm{T})/1.349\right\} \cdot K^{-0.2}, \tag{22}$$

where T is a vector consisting of those $\hat{\tau}^k > 0$ and reflections of these numbers, *i.e.* $-\hat{\tau}^k : \hat{\tau}^k > 0$, σ_{T} is a standard deviation of T, $iqr(\mathrm{T})$ is an interquartile range of T. (22) is often referred to as Silverman's adaptive rule of thumb (after Silverman, 1986); this rule will be used in our study.

Draw a random sample $\left\{\beta^{*1}, ..., \beta^{*K}\right\}$ with replacement from $\left\{\hat{\tau}^1, ..., \hat{\tau}^K\right\}$.

Calculate $\left\{\tilde{\theta}^{*1},...,\tilde{\theta}^{*K}\right\}$ as

$$\tilde{\theta}^{*k}=\begin{cases}\beta^{*k}+h\varepsilon^{*k}, & \text{if} \quad \beta^{*k}+h\varepsilon^{*k}\geq 0,\\ -\left(\beta^{*k}+h\varepsilon^{*k}\right) & \text{otherwise,} \quad \forall k=1,...,K,\end{cases} \tag{23}$$

where β^{*k} is taken from the Step 3; h is obtained from (23); ε^{*k} is a normally distributed random variable $\varepsilon^{*k}\sim N(0,1)$. Then $\tilde{\theta}^{*k}\sim\hat{f}(\hat{\tau})$, where $\hat{f}$ is a kernel density estimator for τ.

Similar statement was proven by Efron and Tibshirani (1993) and Simar and Wilson (1998).

To correct variance, form $\tau^{*}=\left\{\tau^{*1},...,\tau^{*K}\right\}$ as

$$\tau^{*k}=\bar{\beta}^{*}+\frac{\tilde{\theta}^{*k}-\bar{\beta}^{*}}{\sqrt{1+\frac{h^2}{\hat{\sigma}_{\hat{\tau}}^2}}}, \quad \forall k=1,...,K, \tag{24}$$

where $\bar{\beta}^{*}=\frac{1}{K}\cdot\sum_{k=1}^{K}\beta^{*k}$; $\hat{\sigma}_{\hat{\tau}}=\sqrt{\frac{1}{K}\sum_{k=1}^{K}\left(\hat{\tau}^{k}-\bar{\hat{\tau}}\right)^2}$; $\bar{\hat{\tau}}=\frac{1}{K}\cdot\sum_{k=1}^{K}\hat{\tau}^{k}$.

Form $\mathbf{g}^{*}=\left(g^{*1},...,g^{*K}\right)^{T}\in\Re_{+}^{K}$, $\mathbf{B}^{*}=\left(\mathbf{b}_1^{*},...,\mathbf{b}_M^{*}\right)\in\Re_{+}^{K}\times\Re_{+}^{M}$ as

$$g^{*k}=\frac{1+\hat{\tau}^{k}}{1+\tau^{*k}}\cdot g^{k}, \qquad \forall k=1,...,K; \tag{25}$$

$$b_m^{*k}=\frac{1-\hat{\tau}^{k}}{1-\tau^{*k}}\cdot b_m^{k}, \qquad \forall k=1,...,K, \quad m=1,...,M. \tag{26}$$

Using (3) and $\mathbf{g}^{*},\mathbf{B}^{*},\mathbf{X}$, obtain bootstrap estimated values of parameters of (1) $\hat{\theta}_q^{*}\left(\mathbf{g}^{*},\mathbf{B}^{*},\mathbf{X}\right)$.

Using (4) calculate

$$\hat{\tau}_q^{*}=\left\{\hat{\tau}_q^{*1},...,\hat{\tau}_q^{*K}\right\}, \quad \hat{\tau}_q^{*k}=\hat{\hat{D}}_0\left(g^{*k},\mathbf{b}^{*k},\mathbf{x}^{k}\middle|\hat{\theta}_q^{*}\left(\mathbf{g}^{*},\mathbf{B}^{*},\mathbf{X}\right)\right), \ \forall k=1,...,K.$$

Using (11) calculate

$$\hat{p}_{m\,q}^{*\,b}=\left\{\hat{p}_{m\,q}^{*\,b\,1},...,\hat{p}_{m\,q}^{*\,b\,K}\right\}, \quad \hat{p}_{m\,q}^{*\,b\,k}\left(g^{*k},\mathbf{b}^{*k},\mathbf{x}^{k}\middle|\hat{\theta}_q^{*}\left(\mathbf{g}^{*},\mathbf{B}^{*},\mathbf{X}\right)\right), \ \forall k=1,...,K, \ m=1,...,M.$$

Repeat Steps 1–7 Q times to estimate $\hat{\tau}^{*}=\left\{\hat{\tau}_1^{*}\ldots\hat{\tau}_Q^{*}\right\}$ and $\hat{p}_m^{*b}=\left\{\hat{p}_{m1}^{*b}\ldots\hat{p}_{mQ}^{*b}\right\}$ $\forall m=1\ldots M$.

95 middle percentiles of the set of $\hat{\tau}^{*k}$ and $\hat{p}^{*\,bk}_{m}$ represent confidence interval of the ODDF estimates and shadow prices estimates respectively for each DMU.

Finally, we construct bias corrected estimates for parametrically estimated values of ODDF as

$$\hat{\tau}_{BC}^{k}=2\hat{\tau}^{k}-\frac{1}{Q}\sum_{q=1}^{Q}\hat{\tau}^{*k}_{q}, \qquad k=1,...,K. \tag{27}$$

While it was shown that efficiency measures are biased and, thus, require bias correction, presence of bias has not been demonstrated for shadow prices. Nevertheless, we still compute and report bias corrected shadow prices for completeness purposes, but do not rely on these values while discussing the results. Bias corrected shadow prices will be calculated as

$$\hat{p}^{b\,k}_{m\,BC} = 2\hat{p}^{b\,k}_{m} - \frac{1}{Q}\sum_{q=1}^{Q} \hat{p}^{*b\,k}_{mq}, \qquad k = 1, ..., K, \;\; m = 1, ..., M. \tag{28}$$

4.6. Comparing estimates obtained by using different approaches

We obtain three different series of estimates for environmental inefficiencies and shadow prices of undesirable output, namely, parametrically obtained estimates and nonparametrically obtained estimates under two assumptions: VRS and NIRS. It seems logical enough to attempt to compare these estimates to each other to find out if different approaches provide with similar results.

The most direct and the easiest way to compare the estimates is to follow Coelli and Perelman (1999) and calculate correlation indexes between the series of estimates. The obtained values of correlation indexes will indicate whether the DMUs that were determined as inefficient according to one approach tend to be considered inefficient according to the other approach. Similarly, correlation indexes will tell whether the DMUs that had high estimates of shadow prices of undesirable outputs according to one approach tend to have also high estimates of them according to the other approach.

In addition, we may make use of the statistical characteristics of the estimates estimated by using the bootstrap technique. In doing so, we notice whether nonparametrically obtained estimates of ODDF and shadow prices fall within 95% confidence interval around parametric estimates. Should it be so, we conclude that for a particular DMU, the difference between nonparametric and parametric estimates is not statistically significant.

4.7. Analysis of the estimates

As optimizing over many variables without any technical support is both time consuming and leaves much room for errors, we will be using a mathematical software package MATLAB of MathWorks, Inc. for linear programming and bootstrap. The choice was made in favor of this software for many reasons. First, "MATLAB is ideally suited to handle linear programming problems" (Hunt *et al*., 2002). Second, it is an open code program, which allows modifications in the built-in functions should they be necessary. Thirdly, some scholars working in the field of productivity and efficiency analysis are using this software, so the exchange of working codes is possible. Finally, MATLAB can execute basic statistical analysis of the estimates, so it is not needed (in most cases) to use other software for statistical analysis.

Statistical analysis of the estimates will be executed in two main ways.

Firstly, for all estimates we will estimate kernel densities using the reflection method in line with Simar and Wilson (1998). For ODDF we will estimate kernel densities of the monotonically trans-

formed ODDF, namely

$$\delta = \frac{1}{1-\vec{D}_O(\cdot)} - 1. \tag{29}$$

(29) transforms ODDF to the efficiency measure having domain [0, +∞) as $\vec{D}_O(\cdot) \in [0,1]$.

Comparing visual representations of these densities for estimates obtained with different methodologies will provide with some ground for further discussion on comparability of the methodologies.

Secondly, we will analyze shadow prices of pollutants by comparing means of the medium 90 percentiles. If these means happen to be different, we will conclude that a pollutant with a larger absolute value of the shadow price is valued more by most of the societies, *i.e.* most of the societies agree to forfeit more output in order to get rid of one unit of that pollutant.

The study will analyze 96 countries including 27 CITs. The rest of countries contain typical North and South representatives for the purpose of comparing CITs with those.

The list of inputs and outputs for each of the DMUs is represented in Table 1 with description that follows. All data used refers to 1995, the last year when environmental data is available for most of the countries of the world. All values are taken in per year terms.

Table 1. The list of inputs and outputs used in the estimation

Desirable output	Undesirable outputs	Inputs
Economic output *	CO_2 emissions **	Labor *
	SO_2 emissions **	Arable land ***
	NO_x emissions **	Energy consumption **
		Capital stock ***

Notes: * — Taken from WB (2000); ** — Taken from WRI (2004); *** — Adapted from WB (2000).

We employ two specifications, which do not differ in undesirable outputs and inputs, but they differ in desirable output and capital stock. The first specification uses economic output in terms of GDP in international dollars; the second is based on GDP in PPP. Intuition behind using each of the outputs/inputs is provided below.

GDP can be used as a measure of total output produced within the boundaries of the country. As we assume countries to be revenue maximizing DMUs (Axiom 10), GDP can be considered the only good output produced (Axiom 11). Shadow prices of pollutants obtained from Specification I, where GDP is used, can be used as a reference values for monetary rates of payments for environmental damage as well as prices for international environmental trade taken in international dollars.

GDP in PPP. In Specification II, when we take GDP in PPP, we ensure that one dollar is valued by each country in exactly the same way. Thus, shadow prices obtained in Specification II allow cross-country comparison in order to determine, which countries value environmental damage more in terms of purchasing power of money.

CO_2 emissions are resulted mostly by burning various fuels and is considered one of the main sources of the global climate change. CO_2 does not have a significant impact on human health unless in big concentrations (NYSDEC, 2004). The pollutant is selected as an example of the undesirable output, which *a priori* is expected to have *low* shadow price as it does not have any direct impact on people.

SO_2 emissions. The major accounted sources of SO_2 emissions are fossil fuel, including coal and oil fired power plants and boilers, ore smelters and oil refineries. Human exposure to sulfur dioxide can result in irritation of the respiratory system which can cause both temporary and permanent damage. Particulates tend to catalyze the atmospheric conversion of SO_2 to sulfur trioxide (SO_3) which combines with water vapor to form sulfuric acid mist (NYSDEC, 2004). The pollutant is selected as the undesirable output, which *a priori* should have *medium* shadow price as it has limited direct impact on people and human environment through acidic precipitations.

NO_x emissions (includes nitrogen oxides of different nitrogen valency). Nitrogen dioxide (NO_2), a reddish brown gas with a highly detectable pungent odor, is highly corrosive and a strong oxidizing agent. It is produced from the reaction of atmospheric nitrogen and oxygen during high temperature combustion processes such as the burning of fuel (coal, oil, gas) and internal combustion (motor vehicles). Nitric oxide (NO), a colorless, odorless gas, is also a product of combustion and the combination of NO and NO_2 is commonly referred to as NO_x. NO by itself is not usually considered a health hazard, NO_2 can cause inflammation of the lungs and bronchial tubes at high concentrations and less severe respiratory problems at lower. NO_x contributes to haze, reduces visibility, causes serious injury or death to plant tissue, deteriorates fabrics, and forms nitrate salts that can corrode metals (NYSDEC, 2004). The pollutant is selected as an example of the undesirable output, which *a priori* should have *high* shadow price as it has substantial direct impact on people and human environment through forming smog.

Labor is considered one of the major production inputs in the most of production processes. We make estimates based on the total labor force. Thus, increase in unemployment would likely cause increase in inefficiency of the DMU (country).

Arable land is considered one of the production inputs in some production processes. We make estimates based on the arable land available as it is directly involved in production of agricultural output.

Energy consumption was selected as a proxy for all raw materials used. The most energy consuming are those countries producing much of the heavy industrial (polluting) output (Cherp and Salnykov, 2005). We want to debit DMUa for using much energy in the same manner as debiting for overusing other inputs.

Capital stock is considered one of the major production inputs in the most of production processes. We make estimates based on the total stock of fixed capital at the end of the year.

Ideally, as many inputs and undesirable outputs as possible should be analyzed. However, (i) data for many important undesirable outputs (land degradation, water pollutants discharges, *etc*.) is not available for a vast majority of countries and (ii) including too much inputs and outputs to construct referencing frontier may limit power of the methods involved due to small number of observations.

4.8. Summary

In short, the methodology of the study can be summarized by the diagrams provided on Fig. 7 for Specification I. Specification II follows the same general pattern with two major differences: (i) GDP in PPP is used instead of GDP and (ii) we cannot conclude on equilibrium on international pollutants market in Specification II, since shadow prices here are not given in the international dollars.

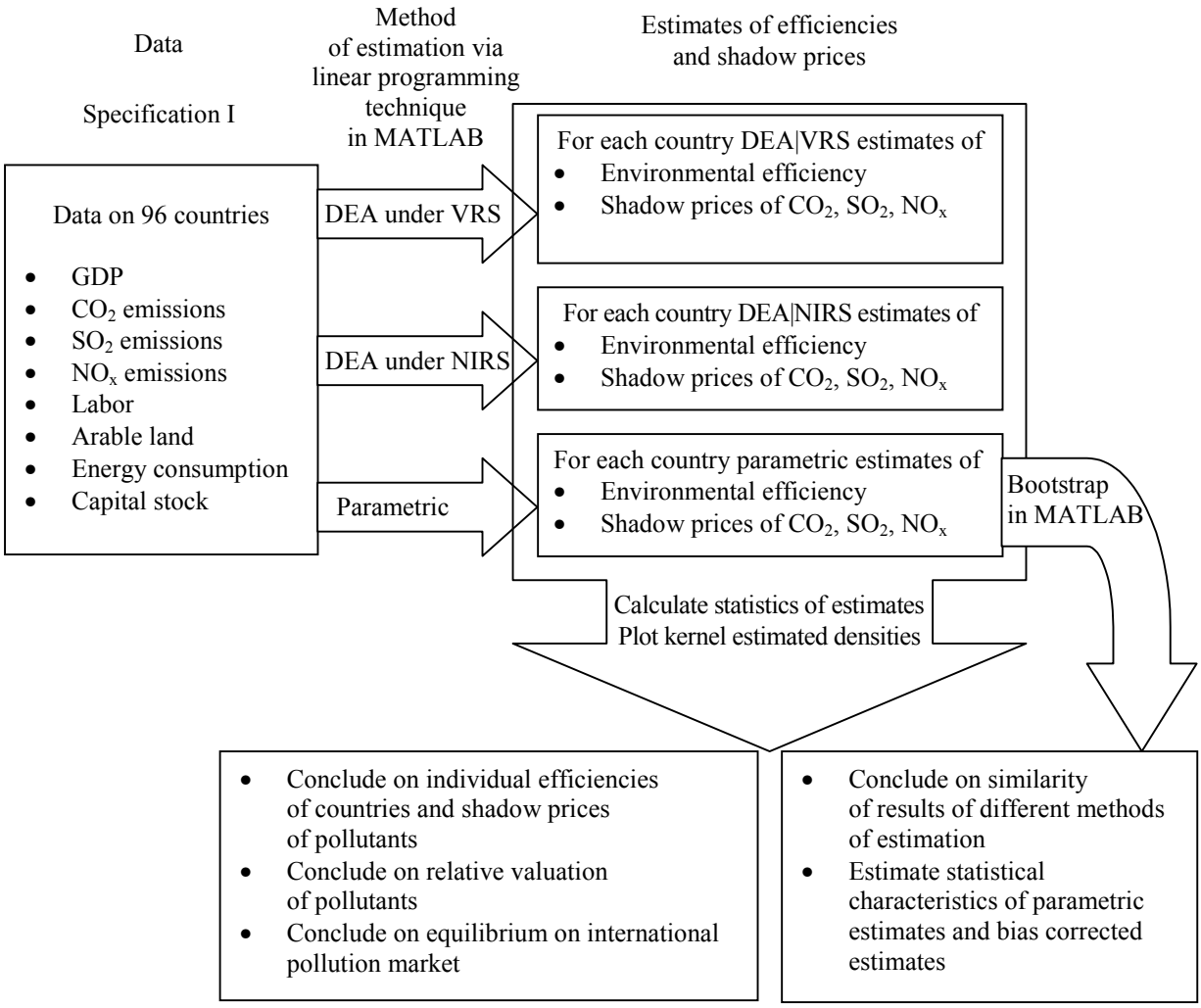

Fig. 7. Flow chart of the empirical analysis

5. EMPIRICAL ESTIMATION RESULTS AND DISCUSSION

#In this section we will present basic descriptive statistics of the data used for empirical analysis, provide and discuss estimation results, while the next section will list our conclusions and policy recommendations.

After we present empirical results of the study, we will provide a general discussion of the obtained results, illustrative examples on the interpretation of the estimates as well as raise questions regarding the choice of methodology (parametric *vs* nonparametric). Unless otherwise specified, we will closely focus in our discussion on Specification I, since Specification II is useful in comparing shadow prices within a single country only. This specification provides with shadow prices in terms of PPP and has a similar intuition as economic GDP in PPP: shadow prices are given in terms of purchasing power of money in a given country and appear to be inappropriate for cross-country comparison purposes.

5.1. Data used in the study

General statistics on the data is provided in Appendix 2.

5.2. Parametric estimation

Running MATLAB code written for the estimation of the ODDF in the *Translog* form resulted the values of the estimation parameters as provided in Appendix 3 (for Specification I) and Appendix 4 (for Specification II).

The estimation of ODDF and shadow prices of pollutants resulted the values given in Appendix 5 (for Specification I) and Appendix 6 (for Specification II).

For the general purpose of referencing, an abstract from Appendix 3 and 5 is provided in Table 2 below.

Table 2. Abstract from Appendix 2 and 5: efficiencies and shadow prices for selected countries (parametric approach, Specification I)

Country	Efficiency	Shadow prices, US$/ton		
		CO_2	SO_2	NO_x
Belarus	0.1707	–74.72	–4463.30	–35361.00
Belgium	0.0361	–1836.00	–81185.00	–1549000.00
United Kingdom	0.0687	–2500.70	–229150.00	–2183700.00
Hungary	0	–389.69	–15261.00	–267560.00

Country	Efficiency	Shadow prices, US$/ton		
		CO_2	SO_2	NO_x
Denmark	0.2034	0.00	–83348.00	–284640.00
Zambia	0.8203	–3578.50	–3382.80	–66157.00
Canada	0.1794	–1607.80	–86064.00	–708710.00
China	0.1633	–1636.90	–68445.00	–1188400.00
Kyrgyzstan	0.0418	–57.75	–8062.10	–18458.00
Latvia	0.1162	–79.76	–7081.80	–53659.00
Netherlands	0	–796.33	–84247.00	–725330.00
Russian Federation	0	–122.97	–3965.20	–48157.00
United States	0	–11161.00	–875500.00	–7863200.00
Ukraine	0.2692	–61.31	–2352.00	–26170.00
France	0.0447	–2213.90	–61396.00	–431520.00

5.3. Nonparametric estimation

The estimation of ODDF and shadow prices of pollutants using nonparametric approach under NIRS assumption resulted the values given in Appendix 7 (for Specification I) and Appendix 8 (for Specification II).

The estimation of ODDF and shadow prices of pollutants using nonparametric approach under VRS assumption resulted the values given in Appendix 9 (for Specification I) and Appendix 10 (for Specification II).

5.4. Statistical characteristics of estimates obtained parametrically

Confidence intervals and bias corrected estimates for Specification I are provided in Appendix 11 (ODDF), Appendix 12 (shadow price of CO_2), Appendix 13 (shadow price of SO_2), and Appendix 14 (shadow price of NO_x) respectively.

Confidence intervals and bias corrected estimates in Specification II are provided in Appendix 15 (ODDF), Appendix 16 (shadow price of CO_2), Appendix 17 (shadow price of SO_2), and Appendix 18 (shadow price of NO_x) respectively.

5.5. Comparing estimates obtained parametrically and nonparametrically

Correlation matrix for estimates obtained in Specification I is provided in Table 3.

Table 3. Correlation matrix for estimates obtained in Specification I

	Parametric	DEA NIRS	DEA VRS
ODDF			
Parametric	1.0000		
DEA NIRS	0.3495	1.0000	
DEA VRS	0.2336	0.7864	1.0000
Shadow prices of CO_2			
Parametric	1.0000		
DEA NIRS	–0.1633	1.0000	
DEA VRS	–0.1880	0.8964	1.0000
Shadow prices of SO_2			
Parametric	1.0000		
DEA NIRS	0.0097	1.0000	
DEA VRS	0.0217	0.5127	1.0000
Shadow prices of NO_x			
Parametric	1.0000		
DEA NIRS	0.0748	1.0000	
DEA VRS	0.0499	0.4267	1.0000

Correlation matrix for estimates obtained in Specification II is provided in Appendix 20.

5.6. Statistical analysis of the results

Joint graphs for kernel estimated densities distributions are provided in Appendix 21 (for Specification I) and Appendix 22 (for Specification II). For the purpose of illustration, kernel estimated densities distributions for estimates of ODDF in Specification I is provided on Fig. 8.

Mean values of the lower (by absolute value) 95% of variables is provided in Table 4 (for Specification I) and Appendix 24 (for Specification II).

Table 4. Mean values of the lower 95% of the estimates: Specification I

	ODDF	CO_2	SO_2	NO_x
Parametric	0.1241	–478.3852	–34130	–264150
Non-parametric NIRS	0.3851	–259.0728	–868.7803	–42685
Non-parametric VRS	0.2847	–133.8549	–3875.2	–6763.7

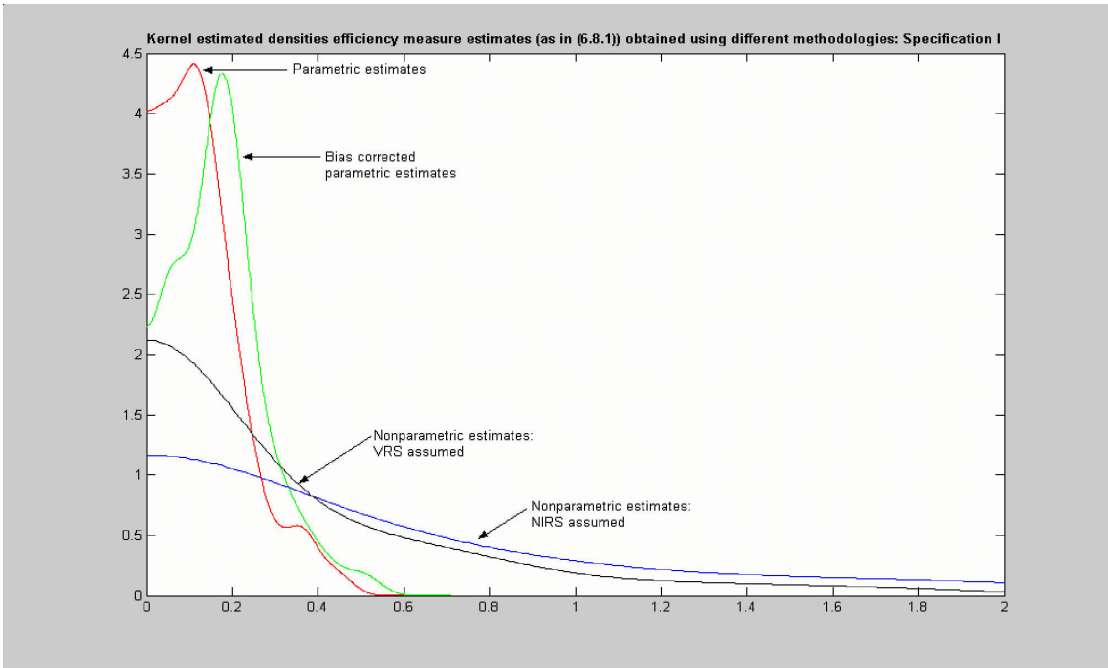

Fig. 8. Joint kernel estimated densities for ODDF obtained using Specification I, transformed as in (29)

5.7. Efficiency measures

Our estimates show that regardless of the methodology, countries on the best practice frontier can be either developed (USA) or underdeveloped (Uruguay). That is because both high GDP countries and low GDP countries are required in order to estimate the best practice frontier. At this, it is by no mean impossible that the best practice country with a low GDP will be also a poor country (*i.e.*, low GDP per capita). An illustration of it can be provided by Fig. 6, where USA would be located on the frontier close to b*, while Uruguay will be also on the frontier, but closer to b'.

In addition, we observe similar variation of efficiency scores within a group of CITs: while some countries may be on the best practice frontier (*e.g.*, Croatia in parametric and Albania in non-parametric VRS framework), others are far from it. However, it must be noted that a number of CITs on the frontier is extremely low for all methodologies (one country under parametric and non-parametric VRS assumption and no countries under nonparametric NIRS). This fact witnesses on a general tendency of CITs to work below their technological potential. The reason for it (most likely) is a wide use of old Soviet-type polluting technologies as well as underdeveloped institutional capacity (*i.e.* ability to address environmental concerns of the society) in these countries, which often accompanies poor environmental performance (Cherp and Salnykov, 2005).

As we restrict measure of efficiency between zero and unity, it has a very simple and intuitive interpretation: it shows by how many per cent a country can increase its GDP and decrease its pollution

being within feasible production combination. We will see the application of this fact in the illustrative example presented later.

5.8. Shadow prices of pollutants

As it was discussed before, shadow prices represent the internal valuation of pollution (by a pollutant) by a given country. *A priori* we expected that those pollutants having more direct and more severe effect on human health should be valued by societies more. Particularly, we expected carbon dioxide to have the lowest (by absolute value) shadow price, nitrogen oxides to have the highest shadow price and sulfur dioxide's shadow price to be somewhere in between.

Such *a priori* expectation is strongly supported in *average* terms for both specifications and each of three methodologies employed. Nevertheless, estimated shadow prices for individual countries sometimes demonstrate different ranking of valuation.

5.9. Illustrative example 1: predicting environmental effect of economic growth

Efficiency measure and shadow prices of pollutants highlight different aspects in fighting environmental degradation. Shadow prices of pollution, which can be interpreted as marginal rate of technical substitution between GDP and a specific pollutant, show a short term changes in environmental quality if GDP changes, while technical efficiency stays the same. Efficiency, in contrast, demonstrates a distance of a given country to the best practice frontier and can be understood as a potential percentage increase in GDP and potential percentage decrease in pollution if a country decides to employ the best possible technology.

Let us discuss the implications of the estimates for Ukraine. Here, for the sake of example, we will focus on parametric estimates.

ODDF value of 0.27 indicates that it is technologically feasible for Ukraine to increase its GDP by 27% and simultaneously decrease the level of CO_2, SO_2 and NO_x emissions by 27% should it decide to use the best-practice technologies. As change of technological process is a long-term course of action, a short-term effect of increase in GDP (or a long-term effect subject to holding to the same efficiency) can be calculated based on the shadow prices of pollutants. Below, we demonstrate step-by-step derivation of the forecasts.

Ukrainian GDP is \$49 bln, CO_2 emissions — 428.7 mln tons, SO_2 — 2.6 mln tons, NO_x — 2.4 mln tons. Shadow prices of the pollutants are as follows: –61.3 \$/ton (CO_2); –2,352 \$/ton (SO_2); –26,170 \$/ton (NO_x).

Suppose Ukraine experiences GDP growth of 1% or \$490 mln, while efficiency remains constant. Ratio of shadow prices, which is equal to marginal rate of technical substitution of GDP for CO_2 pollution tells us that such increase in GDP results

$$\frac{\$490\,\text{mln}}{61.3\ \$/\text{ton}} = 8\,\text{mln ton}$$

or 1.87% increase in CO_2 emissions compared to the original value. Similarly, for other pollutants the increase will be 208 ths tons or 8% for SO_2 and 18.7 ths tons or 0.78% for NO_x. That proposes that Ukrainian economic growth would have the biggest impact on SO_2 emissions, while GDP growth will result an increase of NO_x (the most dangerous) emission in approximately 1:1 ratio.

Interestingly, our estimations are similar to the forecasts of Russian government (whose methods we do not know) with respect to Russian economic growth. In December 2003, Andrei Illarionov, President Vladimir Putin's top economic advisor, commented on Russia's withdraw from the Kyoto Protocol signing: "In those countries we analyzed, each percent of GDP growth is accompanied by an increase of carbon dioxide emissions by 2 percent" (Walters, 2003). Our estimates, in turn, show that Russian growth of 1% of GDP will lead to at least 1.77% increase in CO_2 emissions provided Russian efficiency remains the same. Thus, our estimation methodology provides (at least for Russia) similar estimates as Russian government's methodologies.

5.10. Illustrative example 2: international tradable pollution permit trade

Imagine a simplified version of Kyoto protocol: two countries, Russia and Ukraine, enter an agreement to hold their total CO_2 emission level constant. At this, should any party need to emit more than today, it should negotiate on the price with the other and purchase a permit to emit additional pollution, while the other party should shrink its pollution by the amount sold. Suppose that the government values present gains much more than benefits to future generations.

Assume that technology does not change, but both countries face positive exogenous shock leading to real output growth. Output growth leads to emission increase *ceteris paribus*. At this, according to our estimates, Russia agrees to pay at most $123 for a right to increase its CO_2 emission by 1 ton. In turn, Ukraine agrees to decrease its CO_2 emissions by 1 ton if it is paid at least $61. Since it is clearly in the interests of Russia to pay between $61 and $123 to Ukraine to buy 1 CO_2 ton emission permit, so that Ukraine will shrink its GDP and CO_2 emissions, while Russia will expand both GDP and CO_2 production; both countries will gain from such transaction *ceteris paribus*.

As our model predicts, absolute value of shadow price of a pollutant is negatively related to the GDP level and pollution level *ceteris paribus*. Hence, the absolute value of shadow price of CO_2 increases for Ukraine and decreases for Russia. Should countries face the perspective for more economic growth, the trade of permits continues until shadow prices across countries equalize.

Our simple intuitive illustration leads us to two important conclusions. Firstly, introduction of an agreement similar to Kyoto protocol would lead to equalization of shadow prices of pollutants across countries. Secondly, countries with the lowest absolute value of shadow prices will be tradable permit sellers, while those with the highest absolute value of shadow prices will be permit buyers.

Mean estimated shadow price of CO_2 for CITs is –93 $/ton (with the largest –390 $/ton for Hungary) against world mean of –478 $/ton. Thus, we may conclude that under conditions of Kyoto protocol, CITs will most likely be sellers of pollution permits as it was assumed by UN, while developing the protocol.

Subdivision of the CITs on new EU members plus EU acceding countries[6] and those outside EU provides with the mean estimated shadow prices of CO_2 of –156.8 $/ton (for newly EU entered CITs) and –55 $/ton (for the rest of the CITs) respectively. That allows to extend our argument and argue that countries not heading towards EU will be more active sellers of permits under Kyoto protocol than those, which have entered/entering EU.

Another important implication follows from our analysis. Implementation of Kyoto protocol may cause CITs to decrease their economic output (provided countries don't increase their efficiency). Thus, we may conclude that ratification of the protocol may require additional steps from the CITs' governments to ensure that economic mechanisms do not result suppression of national output in CITs once Kyoto protocol is in force.

CITs will be receiving money exceeding their GDP loss, which is indeed profitable in the short term. However, in the long term these countries would jeopardize their productive factor stock (particularly capital stock) and, thus, receive benefits for the expense of sacrificing future generations' ability to produce.

Therefore, government (national and international) may adopt two amendments to Kyoto protocol *per se*: (i) accomplish pollution permit trading simultaneously with the GDP restructuring, so that GDP growth is achieved by the growth in non-polluting sectors, or (ii) ensure that the money received from the pollution trade goes to improved use of best practice technology (*i.e.* increasing efficiency), not to pockets of individuals.

5.11. Illustrative example 3: developing efficient environmental taxation

Our final example concerns developing environmental taxation on the basis of the estimated shadow prices. Let us depict the derivation of optimal size of pollution tax on the example of NO_x pollution in Ukraine.

Suppose government decides that it is necessary to decrease NO_x pollution from 2.4 mln ton to 2 mln ton. There are two options available: increase efficiency of economy from 0.27 to 0.124 by promoting cleaner technologies or by making NO_x polluters pay a tax and, thus, shrinking both GDP and NO_x production. Here we will review second choice, since it is related to estimated shadow prices.

Suppose Ukraine is not going to change its efficiency and undesirable output emissions level others than NO_x. Then (5.1.1) leads to the following constraint:

$$\begin{aligned}\alpha_1 \ln g + \beta_3 \ln b_3 + \frac{1}{2}\alpha_{11}(\ln g)(\ln g) + \ln\ b_3\left(\sum_{m=1}^{2}\beta_{m3}(\ln b_m) + \frac{1}{2}\beta_{33}(\ln b_3)\right) + \\ + \frac{1}{2}\sum_n \delta_n (\ln g)(\ln x_n) + \frac{1}{2}\ \ln b_3\ \ \sum_n \varepsilon_{3n}(\ln x_n) + \frac{1}{2}\sum_m \zeta_m (\ln g)(\ln b_m) = const.\end{aligned} \tag{30}$$

[6] Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovak Republic and Slovenia (new EU members) and Bulgaria and Romania (EU acceding countries).

Calculating (30) for current values of outputs and inputs provides with a value of constant –2.2893. Substituting $b_3 = 2$ instead of 2.4 and solving for g provides with a new level of GDP of \$39.3502 bln. Finally, solving (5.2.7) with new values of NO_x and GDP provides a new estimate of shadow price of NO_x equal –63,111 \$/ton. In other words, in order to lower NO_x to a level of 2 mln ton, the government needs to make the society to value 1 ton of emission by \$37,000 more, *i.e.* impose a tax of \$37 per 1 kg of NO_x emitted.

Three important reservations should be made with respect to calculating environmental tax rate using this methodology. Firstly, the government needs to determine a target level of emissions *ex ante*. Secondly, the methodology of calculation is mathematically cumbersome and is not, by any mean, transparent, which is a desirable property of any taxation system. Thirdly, the taxation rate calculated is a *country-level* rate, which will be (almost for sure) different from the optimal levels of taxation for individual firms (as each firm may have different shadow prices).

With respect to the first complication, we must acknowledge that the government should make a decision on the target level of emissions based on its judgments on what is the socially desirable level of pollution, which is not an easy task. With respect to the second complication, the calculations should be made once by authorities and later altered should target level of emissions change: general public can be given just a final rate of taxation.

The third complication is the most crucial, but still solvable. Two solutions can be proposed. The first is to impose taxation on the country. Such a tax can be levied by the international government (*e.g.* the UN). For example, by imposing a tax on Ukraine of \$37 per 1 kg of NO_x emitted, the UN can expect that Ukraine will shrink its NO_x emissions to the level of 2 mln tons per year. The second solution (which also can be considered as a government's response to the first option executed by the UN) involves additional estimations executed by the government on the firm-level data. Following our methodology, the government can estimate shadow prices of pollution for the firms responsible for the largest share of pollution in the country (*e.g.* 95%). Once these prices are estimated, the government selects a level of the tax (*i.e.* the number by which the shadow prices should be increased) so that to shrink the total emission level by a desired number (0.4 mln tons in our case).

Finally, we must acknowledge that the current example related to the use of our estimates in establishing size of environmental taxation is rather rough and needs further consideration and motivation, which can be done by the further studies. Therefore, this example should be considered as one of the possibilities of building the environmental policy, although not an ultimate.

5.12. Comparing parametric and nonparametric approaches

We use kernel estimated densities of the estimates and correlation matrices as instruments, which can potentially provide us with a red flag on statistically significant differences in the estimates. Should such signal be received, we must study statistical characteristics of the estimates to determine if the estimates are different indeed.

Comparison of kernel estimated densities for ODDF estimated under three methodologies provides a signal that estimates obtained under different methodologies may be statistically different. Very low correlation coefficients between estimates obtained from different methodologies confirm concerns on incompatibility of the methodologies. For these reasons we need to compare the methodologies based on the statistical characteristics of the estimates.

As we can see from the estimates, out of 96 values of estimated ODDF value under nonparametric NIRS assumption only 22 fall within 95% confidence interval of parametric estimates. The same number for the estimated ODDF values under nonparametric VRS assumption is even lower: only 18 fall within 95% confidence interval of parametric estimates. Similar pattern is common for shadow prices and Specification II.

Based on this, we may argue that parametric and nonparametric approaches give statistically different estimates. For a long time these two techniques have been used interchangeably with more preference given to nonparametric when estimating ODDF and more preference given to parametric when estimating shadow prices. However, bootstrap-identified statistical characteristics of parametric estimates point out that it is needed to pay more attention to the choice of methodology while deciding between these two approaches.

What can be the reasons for such drastic differences in the results? Firstly, the parametric approaches allows to envelope data within a smooth hull restricted by certain parametric form, while nonparametric does it using a piece-wise linear estimate for technology set. Naturally, as these two hulls do not coincide, this difference is one (but by no means the main) reason for differences in estimates. Secondly, nonparametric approach does not allow modeling bounded output set, while parametric does.

A natural question, which arises after problems with compatibility of approaches are identified is: what approach should be trusted more. In estimating ODDF nonparametric approach is widely used and there is no specific reason to prefer parametric approach over nonparametric here. Moreover, since parametric approach is capable to misidentify inefficient DMUs as efficient, probably, we should rely more on nonparametric estimates while estimating ODDF only.

Nonparametric approach, however, turns to be highly inconvenient once we start estimating shadow prices. The methodology we employ allows estimating a shadow price, which can be nonunique due to existence of multiple solution to the linear programming task (this refers to the points, which are located on the kinks of the piece-wise linear frontier). The issue of identifying other solutions of the problem is technically complicated and currently solving this question is in progress. Therefore, until the issue is solved, using parametric approach for estimating shadow prices is, probably, the most reasonable choice.

Finally, nonparametric approach is not a convenient choice when using bootstrap to estimate statistical characteristics of the estimates, when the sample is small, which is the issue in our case.

One of the solutions to the above problems with the methodology choice would be an option of employing Stochastic Frontier Analysis (SFA) approach, which is convenient, when taking derivatives

(to estimate shadow prices), but also allows for statistical noise with certain parametric structure, which may absorb some discrepancies missed by the parametric approach. As nobody has done SFA when some outputs are undesirable, setting up theoretical framework and model is a time consuming process and, certainly, is a topic of a separate paper.

6. CONCLUSIONS AND POLICY RECOMMENDATIONS

This final section will briefly outline general conclusions of the work, policy implications based on our findings and some limitations of the current research as well as recommendations for the future studies in the field.

6.1. Conclusions

The obtained estimation results clearly demonstrate that with respect to the technical efficiency, both rich and poor countries can turn out to be fully technically efficient. At this, transitional countries mostly take positions of the inefficient. Ukraine seems to be far away from its technical potential being more than two times inefficient than the mean value of the indicator. That clearly points on a significant perspectives our country has in moving towards production possibility frontier.

As the value of the present work for the public policy lays mostly in the domain of the shadow prices as estimates for an efficient environmental taxation, we must note that the estimation results point out that CO_2 is 'the least expensive' pollutant, while NO_x being 'the most expensive' one. Such result is not surprising, as any society would value an undesirable output with an indirect harm (in our case a greenhouse gas affecting global climate) less then an undesirable output having a direct influence on the human health (such as NO_x).

The values of the shadow prices obtained from the estimation can be used as the proxy values in setting efficient environmental tax rates. At the moment, (as far as it can be judged from the personal environmental auditing experience) in Ukraine these rates are far below the estimated values. That provides us with a conclusion that in order to meet the societal valuation of the environment, the government should inevitably raise the rates for air pollutants.

Our conclusions in the field of international pollution trade indicate that should any agreement similar to Kyoto protocol be in force, under assumption of unchanging technology CITs will be major pollution permit sellers. By doing so, CITs will find more beneficial to gain revenues from selling permits than from the own economic development, thus sacrificing perspectives to build up capital stock needed for future generations for the instant revenues for current generations subject to no structural changes in GDP. This conclusions allows us to argue that Kyoto protocol *per se* leads to distortions in the intergenerational aspect of sustainability in transitional countries; thus, additional restrictions on this agreement should be put to secure against these distortions or alternatively national governments should ensure that interest of the generations to come are not hampered. Such restrictions are discussed in the policy recommendations section.

Färe *et al* (1993) indicated that unequal values of shadow prices among DMUs point on the inefficient allocation of resources. For this reason, our estimates show that the global economy's wealth and pollution is allocated inefficiently. One of the ways to change this situation is to set environmental taxes using shadow prices estimates as reference values and allow invisible hand of Adam Smith to lead all countries towards a common valuation of environmental resources.

Kernel estimated densities, correlation matrices and confidence intervals of the estimates obtained using smooth homogeneous bootstrap procedure revealed that nonparametric and parametric approaches generally lead to statistically different estimates, although before these techniques were used interchangeably with little attention paid to justification of the choice of approach.

6.2. Policy recommendations

We provided three illustrative examples, how our empirical findings can be useful in developing national environmental and development policies.

Our first illustrative example showed how our estimates can be used in forecasting environmental outcomes of economic growth within a short run based on the estimates of the shadow prices. Estimates of the efficiency measures allow concluding on technological feasibility and scale of potential simultaneous increase of GDP and decrease of environmental pollution. Particularly, we can argue that practically all CITs including Ukraine are away from the best practice frontier, thus have promising long-term perspectives in simultaneous increase of GDP and decrease of pollution, should they improve the technologies in use. Moreover, below-average shadow prices of most of the pollutants in most of the CITs enable us to conclude that decreasing environmental degradation in these countries requires much less sacrifice of economic output than in the developed countries even if efficiency is not increased (*i.e.*, in the short term).

Second illustrative example shows implication of our study for determining a range of prices for international emission trade on the example of an agreement similar to Kyoto protocol. Besides conclusions on prices, our analysis implies that Kyoto protocol may be deeply unsustainable for transitional countries in a sense that it hampers their potential for economic growth and, thus, jeopardizes ability of future generations to develop. That does not imply that Kyoto protocol is undesirable for CITs: current and future may still benefit from the emission trade subject to preventive measures taken by the national governments. Policy recommendations on this issue can include but are not limited to the following:

- ignorance of Kyoto protocol by CITs;
- amendments to the protocol restricting international pollution trade only within separate groups of countries, *i.e*. NIS can trade only with NIS countries, EU can trade only with EU countries, NAFTA can trade only with NAFTA countries, *etc*.;
- steps of national governments aimed on putting quotas or otherwise limiting sizes of permit sales so as to soften the protocol's effect.

The most proactive responses of national governments to the protocol that allow enjoying the benefits of it, while still securing against potential harms, would be:

- structural changes in the economy aimed on achieving economic growth due to growing non-polluting sectors (*e.g.* IT industry, academia, *etc.*); and
- ensuring that the payments received from the pollution trade go to increasing environmental efficiency of the existing technologies, not to pockets of individuals.

Our third, final example illustrates how to determine the optimal size of environmental taxation based on the *a priori* knowledge of the socially desired pollution level and estimated values of shadow prices. Although this methodology is not as transparent as a 'perfect' taxation can be, it still allows reaching goal of the society. We demonstrated how a desired level of pollution can be achieved by using both taxes imposed by the international government on the country and by the national government on the domestic firms (subject to additional estimation executed). However, in the case of this example, some additional (theoretical) studies should be executed in order to demonstrate, how the estimates of the shadow prices can be used in establishing environmental taxation.

In general, this study has promising implications for environmental policy. However, these implications may be more sound should further efforts be invested in the further research in the field.

6.3. Limitations of the study

Our work took a static approach to the problem. In addition, it worked with a rather outdated set of data. Here, we consciously sacrificed recentness of the data for the size of the sample as most of the recent datasets available concern specific limited groups of countries and none of them include CITs. Therefore, should any, more recent big sample become available, it will be possible to update our results and calculate dynamic efficiency indices (*e.g.* Malmquist index). In addition, it would allow using bootstrap technique with respect to the nonparametrically obtained estimates.

Such extension will possibly also enable to analyze a bigger number of undesired outputs subject to availability of data, since number of outputs is closely linked to the size of the sample.

Our study also reviewed big countries (*e.g.* Canada, China, Russian Federation, USA, *etc.*) as single DMUs, while it might be more proper to subdivide them by provinces, oblasts, states, *etc.* to allow for heterogeneity within countries subject to availability of data. Another comment on heterogeneity within DMUs implies that our study did not attempt to identify shadow prices of individual micro-level DMUs within each country, thus providing only with an aggregated average estimate of the shadow prices and environmental efficiencies.

Finally, our study did not allow to make a confident choice between parametric and nonparametric techniques. This task is clearly a subject of a separate study, which can be only executed after other techniques are studied (specifically, SFA approach).

6.4. Recommendations for further research

Our research was, probably, the first attempt to apply productivity analysis in the presence of undesirable outputs to macro-level data and compare parametric and nonparametric techniques when some outputs are undesirable. Therefore, it is natural that, in addition to addressing the initial questions, it raises additional questions and opens perspectives for further research in the field.

We believe that one of the necessary prerequisites for the further studies is deciding between nonparametric and parametric approach, since their results may be statistically different. In addition, one may attempt to approach the problem via Stochastic Frontier Analysis technique, which is a previously unexplored field. The results obtained then can be compared to the parametrically and nonparametrically obtained estimates to check for compatibility of estimates. In addition, the issue of multiple solutions in identifying shadow prices in nonparametric framework should be solved.

It may be also an interesting issue to check if the choice of directional vector changes the results qualitatively. Should it be so, this choice should be considered crucial in the future studies.

Once the choice of approach is justified, future studies in the field may attempt to analyze larger samples of macro-level panel data in order to estimate dynamic productivity indexes.

The estimates of shadow prices may be applied toward creating an environmental analogue of economic GDP, which is a sum of products of pollution levels and the respective shadow prices. Difference between economic GDP and the obtained measure will display the sustainability of the country in line with the weak sustainability concept. Should it be nonnegative, the country is weakly sustainable and weakly unsustainable otherwise.

Moreover, our estimates can be used in estimating environmental demand function. Previously it was an unsolvable issue, mostly because of impossibility to estimate country-level shadow prices.

Finally, there is a need for a theoretical study, which would demonstrate a sound methodology of using shadow prices of pollution as reference values of environmental taxation.

In general, this research opens a lot of perspectives in the future research activities, which we will hopefully attempt to address in our future studies.

APPENDICES

Appendices contain mostly technical information and large volumes of estimates. Interested readers can download appendices from http://www.sfu.ca/~msalnyko/pdfs/wp_eerc/appendices.html.

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