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Efficiency and productivity in presence of undesirable outputs

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Introduction and summary

The thesis is composed of a short introduction aimed at introducing the topic and reviewing the literature, then three empirical articles are proposed.

The first part tries to explain the main motivation of the present work, underling the importance of including undesirable outputs and externalities in the productivity estimates. Not only the case of environmental regulation is considered as a driver of the field literature: multiple objectives require the partial revision of the standard concept of efficiency considering priorities of the producer. Traditionally the case of pollution is the main problem considered: from a microeconomic point of view the first attempt to internalise bad outputs into productivity occurred in Pittman (1983) with some methodological difficulties. Scheel (2001) tried to summarise the most used model in efficiency evaluation, but in many papers the formalised technology was not representative reality. The main revolution occurred with the introduction of the so called directional distance function (DDF) by Chambers *et al.* (1996). That definition of distance allowed to model production process in the right way and to discredit firms that produce undesirables by modifying only productivity indexes. Theoretical properties of that generalisation of output and input distance functions are analysed in Chambers *et al.* (1998) and Färe and Grosskopf (2000). Applications of that concept using linear programming methods are growing particularly in the environmental field.

In the first article the eco-efficiency level of a group of Italian firms, operating in 5 industrial sectors, are computed using the DDF framework. Data come from two different databases: the European Pollutions Release and Transfer Register (E-PRTR), that collects data on air and water pollution at plant level for 89 chemicals in some particular sector, and the AIDA database that contains all economical variables derived from balance-sheets. Starting from inputs and outputs data and applying DDF approach, ecological-economical performances of around 180 Italian firms are computed, in both regulated and unregulated frameworks. Results are analysed in a second stage phase, where the determinants of environmental performances and regulatory impact are investigated applying Simar and Wilson (2007) methodology. Conclusions underline that the sector-specific effect on eco-efficiency and opportunity costs of regulation will disappear when individual characteristics of firms are considered. A major difficulty in dealing with environmental constraints emerges for small and medium firms.

The Second article considers the scientific production by CNR's research institutes: they produce a portfolio of products characterised by different scientific profile. The hypothesis is that there are 2 category of scientific outputs: researchers and institutes try to maximise only one of them, but the other cannot be reduced or eliminated without a resources' drop. Data on funds and researchers are collected by public balance sheets and integrated with scientific outputs information. This allow to estimates an efficiency model applied to the whole CNR: all the departments are included and the field heterogeneity is captured through the complete output portfolio. The effect of fund cutting from the government is estimated and Total Factor Productivity (TFP) growth is computed. Chung *et al.* (1997) propose an extension of Malmquist index, based on an intertemporal comparison of frontiers, called Malmquist-Luenberger (ML), able to consider bad outputs. Obtained estimates allow to verify different hypothesis: from the consistency and novelty of results to the TFP growth trends and concluding with quantification, in term of unpublished scientific papers, of the fund cutting occurred after the 2003's reform. Finally the third article is focused on the comparison of firms from Italy and Germany within the chemical industry, a mature sector where testing for the validity of Porter's hypothesis could be particularly interested. Data for inputs, outputs and pollution are collected for a small sample of around 40 firms from both countries and applying DDF, environmental performances and TFP growth are estimated focusing on the differences from the two economical system. A relatively new methodology is proposed to compute TFP growth indexes by assuming a sequential idea of technology in presence of pollution (Oh and Hesmati, 2010). The estimations reveal an higher eco-efficiency level for Italian firms, also if they are more pollutant in absolute term. TFP growth, that take into account reduction in emission levels, reveal a more favourable trend for German firms which at the end of period reach an eco-efficiency level similar to their counterparts. Finally a formal test for the Porter's hypothesis lead to a rejection, revealing the absence of a positive relationship between initial regulatory costs and observed TFP growth rates.

The reminder of the thesis is organised as follows: chapter 1 reviews the literature, chapters 2, 3 and 4 coincide with the previously mentioned articles.

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Chapter 1

Efficiency and productivity analysis in presence of undesirable output: an extended literature review

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Abstract

During the past 20 years the interest on productivity measure able to consider undesirable outputs in production processes stimulated an increasing literature on that field. The number of paper written is impressive and this review is aimed to draw a detailed picture of the phenomenon on the basis of previous literature collections. Many recent paper are analysed and classified on the basis of definition from previous works. Finally an extended and probably exhaustive collection of papers dealing with the concept of directional distance function (DDF), one of the most suitable tools for undesirables, is proposed as a conclusion.

JEL code: D24, Q53
Keywords: Undesirable Outputs, Linear programming, Efficiency and productivity

1.1 Introduction

In the recent years the attention on environmental protection and sustainability of economic activities is continuously raised. A large number of new constraints are imposed by regulation with the aim of increasing environmental performances especially of firms involved in such production processes which are characterised by significant production of pollutants. Entrepreneurs and managers but also stakeholders and consumers are paying increasing attention on what are called green performance indexes: this create a strong demand for scientific research aimed at creating productivity indexes or more generally performance measures able to include both economical and environmental aspects of firms behaviour. Some initial ideas of the 70's and 80's, when pollution control was considered only as a burden on firms, were partially overcome during the 90's with the so called Porter's hypothesis. The main idea was that emissions are a sign that resources have been used incompletely, inefficiently or ineffectively (Porter and Van der Linde 1995) then environmental regulation and pollution reduction could be seen as a sort of stimulus for firms to the adoption of new technology. These are so called win - win opportunities when both green and economic performance get better and also innovation is stimulated. Each consideration in every direction is strongly dependent on the methodology adopted to investigate the phenomenon and this underline the importance of performances measurement. The main point in all policy and management consideration regarding particular sector cannot ignore the presence of pollution or the joint production of undesirable outputs in general. Moreover the effect of environmental protection is so pervasive to influence managerial and entrepreneurial action at each level, forcing to consider overall productivity measure. The emerging methodological issue concerns the best method to jointly considerate economical and environmental factors to create global indexes of performance. Such indexes are also connected to the need of understanding which kind of effect ”new” regulation had on agents' behaviour, in this case firms. The effect of these changes could be wider than a simple measure of additive costs imposed by the normative: that is only the ”direct effect” but other kind of variable must be considered. In the first period the literature's attention was on the aggregate effect of the normative change and on the relative cost: especially during the 80's environmental rules were considered as the main guilty of the Slowdown in productivity growth rate. In one of the early paper on this issue Denison (1979), by estimating the incremental total cost from new environmental rule, found a significant negative contribution to the productivity fall from a macro economical point of view. In fact abatement control expenditures miss a lot of different costs which are strictly connected with environmental factors one of the best way to include all possible effects it's to measure the changes in productivity and in particular in total factor productivity (*TFP*). But here another problems arise: how to measure in the correct way total productivity? That is a big task in all the field where productivity is a key factor but became a huge problem when emission and pollution must be taken into account as a consequence of a specific normative[1]. Firms and in general Decision Making Units must modify their decision by considering other outputs for which prices don't exist. As mentioned before, classical measure of *TFP*, over time or between economic units, substantially fails in representing the real situation: efforts in reducing bad outputs are ignored because only products with positive prices are included in calculation. The problem of bad outputs was firstly considered in productivity growth accounting by Pittman (1983) where the framework by Caves *et al.* (1982) was extended through the estimation of a negative shadow price for each pollutant. This estimation could be source of big distortions as was underlined later by Boyd and McClelland (1999) and to partially avoid the problem three different sets of data are used to obtain estimations of shadow prices. All data were based on the normative compliance costs provided by engineers or on pollution abatement costs. Empirical findings suggested that productivity levels were significantly different when pollutants were taken into account. The main problem of Pittman's approach was that information about abatement costs were rarely disposable and often not very precise: abatement control expenditures miss many costs such as time spent by managers complying with environmental regulation, redesigning production process or changing the input mix, increasing maintenance and increasing attention into measuring and reporting emissions as underlined later in Berman and Bui (2001). Some sophisticated methodologies start to be widely used in standard setting to create relative measure of productivity, like Data Envelopment Analysis (*DEA*) or Stocastic Frontier Analysis (*SFA*). Both instruments suffer from the same limitation, because both methods are created to credit firms which produce more outputs using inputs. They are adapted or extended to analyse environmental problems during the 80's and 90's, a period of high production of paper analysing environmental issues. It is possible to find 3 literature reviews on efficiency and productivity models applied in this field. Cooper *et al.* (1996) analyse more than 100 empirical papers dealing with the problem of air emission ascribable at operating research methods. Tyteca (1996) propose a brief overview of the main methodology applied do deal with pollution production, the focus was on linear programming methods. Finally Zhou *et al.* (2008) track more than 100 papers written between 1983 and 2006 more which involve energetic or environmental issues. Focusing on this latter review is possible to underline how some assumptions are becoming commonly accepted such as weak disposability of undesirable outputs. The reminder of the paper

[1]This idea extend what Christainsen and Haveman (1981) say about productivity measure at aggregate level

try to present, step by step, a simplified picture of the main empirical strategy applied in recent papers, categorising them into some of literature-pillars identified early. Section 1.2 summarises the most basic methodology to get eco-efficiency scores, while section 1.3 lists two hypothesis commonly accepted in most recent works. Section 1.4 shows two recent and useful methodology applied in some papers, but characterised by some computation difficulties through linear programming. Finally section 1.5 presents the directional distance function model and propose an extended literature review of a large number of studies applying that tool. The main advantage and limits of the latter approach try to conclude this survey, underlining some new approaches.

1.2 Discussion on basic DEA models

In standard DEA efficiency models decreasing of outputs are not allowed, but just input could be reduced. When an undesirable production results such as pollution is obtained, inefficiencies increase with it. This simple intuition motivates the methodological problems which arise with the inclusion of emission realises into standard production models. On the basis of Scheel (2001) some direct and indirect methods of including undesirable products could be identified. In the first group are placed all the approaches that directly modify assumption on the output sets, while in the second methods based on data transformations. Let $x = (x_1, ..., x_N) \in R_+^N$ be a vector of inputs, $y = (y_1, ..., y_M) \in R_+^M$ a vector of good outputs and $b = (b_1, ..., b_J) \in R_+^J$ a vector of bad outputs such as pollution, finally let the corresponding capital letters represent relative matrixes. Observations come from K DMUs, k represents a particular subject, while capital letters X, Y and B condense data matrix, in the form NxK, MxK and BxK.

1.2.1 Bad outputs as inputs or similar

Including environmental factors among inputs seems to be the first step to create more comprehensive measure of performances, but the resulting DEA model does not reflect the true production process. Starting with a classical DEA model where inputs and undesirable outputs are split for simplicity:

$$
\begin{aligned}
EPI &= \min \lambda \\
\text{s. t.} \quad y^k &\leq Yz \\
Bz &\leq \lambda b^k \\
Xz &\leq \lambda x^k \\
z &\in R_+^k
\end{aligned}
\tag{1.1}
$$

The main advantage relies in the fact that data do not require any transformations and pollution is directly minimised. However that approach is not so common because the implicit estimated technology is exactly the same of including undesirables among outputs with a negative sign. All the constraints remain linear and the underlying distance concept remain radial. This is one of the main disadvantages: the potential reduction factor is expressed in input orientation, but undesirable byproducts are outputs (Dyckhoff and Allen, 2001). The efficiency ranking is very similar to what obtained by direct methods based on data transformations, only when transformation is non-linear results change (see next paragraph). Some recent application of that approach still exists; Telle and Larsson (2007) estimate the differences in productivity growth measured with Malmquist indexes in both a regulated and unregulated framework. They identify two categories on inputs, one normal and one environmentally detrimental, both included as inputs to be minimised in a standard DEA model with input orientation. On that basis two set of Malmquist indexes are derived and compared to obtain a differential of productivity growth due to environmental protection efforts. Yang and Pollitt (2009) estimate the performances of Chinese coal-fired power plants by applying a multi-stage DEA model. They include bad outputs adding a separate linear constraint for them, but the intensity variable used for minimization is the same of inputs. This implies that the separated treatment of undesirable byproducts is only spurious and they are practically considered as inputs. Picazo-Tadeo and Reign-Martinez (2007) propose a different model that exploit property of short run profit function, assuming some inputs fixed and other variables. Among them nitrogen consumption represents a sort of bad input to be minimised, where profits are maximised under a constraint on nitrogen consumption and without it. Standard DEA procedure is applied to get estimates for both regulated and unregulated scenario, showing the existence of win-win opportunities.

1.2.2 Bad outputs with negative sign or in transformed form

Another intuitive possibility to treat undesirable outputs asymmetrically, is transforming their observation data in a proper way. In standard output oriented DEA models, all outputs are maximised keeping inputs unchanged, then if bad output data are properly transformed, this could correspond to their minimisation in original terms. All monotone negative transformation could be applied to reach that objective. Scheel (2001) tried to sum up the most used transformations, exploiting the main implicit assumptions on disposability which characterise each method. In many cases linear negative transformations of bad output data such are applied for that scope, building a technology very similar to the introduction of pollution among inputs. but they lead to a production function that is not representative of the reality. Other kind of transformation introduces problems of non linearity, then classical DEA models cannot be easily applied. Among the last application of that approach Fleishman *et al.* (2009) includes pollution as negative outputs, then with a negative sign to pollution quantities analysing US power plants. Second stage analysis of results performed using Tobit underline the strong linkage between regulation and efficiency. Example of additive inverse such $f(b) = -b$ are applied in Seiford and Zhu (2002) with result mainly in line with hyperbolic efficiency measures. Other case of linear tranformation are kind of translation $f(b) = b + K$ as suggested in Ali and Seiford (1999), where the constant K is a sufficiently large scalar above the maximal observation on bad outputs. Finally a multiplicative inverse approach like $f(b) = b^-1$ appears in Lovell *et al.* (1995), but introduce non-linearity issues related to non-linear transformation of data. The main disadvantages of that methods rely in the transformation of data an artificial process that does not allow to well represent production process. Moreover original scale and intervals of transformed or translated data get lost and, in case of reciprocals, zero observation become missing values.

1.2.3 Purely environmental performance

The final intuitive solution to maintain a quasi radial definition of distance relies in changing the definition of productivity with a specific focus on environmental aspects. In this way production process remains well represented through the introduction of an extra pollution variable into the production process treating it as an additional input or, in this case a weakly disposable outputs [2], in other cases emissions are treated and minimised

[2] Specific explanation of weak disposability is given in next section

separately to get pure environmental performance measures. In the majority of the cases efficiency indexes remain radial, if one accept to consider only the bad outputs space, and the underling distance function does not change significantly in respect to the standard DEA approach. Starting with the simplest approach, Tyteca (1997) provide a measure of pure green performance, giving a standardised index characterised by a low discriminating power. Estimated linear programs to get Environmental Performance Index (EPI) appear as follow:

$$\begin{aligned} EPI &= \min \lambda \\ \text{s. t.} \quad y^k &\leq Yz \\ \lambda b^k &= Bz \\ Xz &\leq x^k \\ z &\in R^k_+ \end{aligned} \tag{1.2}$$

Noticing that in this case weak disposability is assumed: it is clear from the equality constraint on bad outputs, that in case of standard assumption on the output set became an inequalities. Very similar approaches are followed in some different way by Reinhard *et al.* (2000) who estimate EPI in both deterministic and stochastic framework. Färe *et al.* (2004) give a first theoretical insight for the analysis of EPI maximisation in aggregate countries comparisons. Färe *et al.* (2006) analyse the EPI by introducing a sort of bad output distance function and analysing Malmquist indexes computed over that distance in both articles. Linear programs solved are very similar to the previous, but through a maximisation, where the increasing factor on bad products is $1/\lambda$. Bevilacqua and Braglia (2002) set a similar LP problem, but they obtain purely environmental performances by just including emissions as inputs and excluding capital, labour and other classical variable. Their study represents the only published work dealing with environmental efficiency of Italian firms. Zhou *et al.* (2007) extend this idea by adding a non radial feature, underling how a decision maker or a policy maker could prefer reduction in some particular undesirables. In this case a normalising factors is applied to each pollutant categories in order to modulate particular strategies, avoiding implausible equal efforts in reducing more dangerous substances. Coelli *et al.* (2007) propose an alternative method of controlling for phosphorus overproduction in Belgian pig-finishing farms. Their approach do not include additional variable, but operates through more reliable material balance conditions, getting immediate cost reductions strategies from pollutant reduction. Zhou *et al.*

(2010) still extend this approach by including 2 categories of inputs and outputs, but just an environmental performance index is calculated, only through emission minimisation. Principal advantages of these techniques are the possibilities of estimates using standard DEA solvers: from a conceptual viewpoint inputs, outputs and undesirables are separated, but many problems come from their low discriminating power. The number of inefficient unit is very low and for the big majority of the analysed sample performance cannot be estimated. Moreover economical aspects are totally ignored, then only pollution reduction drive productivity and efficiency changes.

1.3 Direct methods and two hypothesis commonly accepted

This methods are more focused on the formalisation of production possibility set on light of undesirable outputs. On the basis of the new output set identified, more complete and reliable efficiency measurement are computed.

1.3.1 Null jointness

Bad outputs such as pollution are considered as a sort of byproduct results of the main production process aimed at producing desirable outputs. These two categories of results come together, then possibilities of avoiding bads rely in the decision of not producing goods. In other words it is impossible to observe a positive amount of good outputs without observing also a positive amount of bad outputs. Hence the following formalisation:

$$(y, b) \in P(x) \text{ and } b = 0 \Longrightarrow y = 0 \tag{1.3}$$

represents the so called Null Jointness assumption. This is a condition normally accepted on the output set from the branch of the literature applying direct methods of bad output inclusion.

1.3.2 Weak disposability hypothesis

Accepting that good and bad outputs come together it is not sufficient, because something must be said on the fact that reductions of bads are difficult. Standard assumption of free disposability on outputs cannot be accepted for the case of pollution in a regime of environmental protection. In fact assuming free disposability imply that outputs could always be reduced without cost, but this is not representative of reality in case of emissions. In particular each reduction cannot occur for free, it is costly in technological terms because imply different equipment or more expensive inputs. If the orientation is based on outputs, then inputs are maintained fixed, the only way to observe bad outputs reduction was via good outputs cuts. The classical assumption of strong disposability could only be accepted on the subset of desirable outputs, because if extended to bad outputs imply free reductions possible, compatible only with a regime of absence of environmental protection. In the latter paradigm the absence of regulation does not force subject to consider undesirable outputs as a relevant variable and they could be indifferently increased or reduced, without costs. More than the 25% of previous paper on EE analysed by Zhou *et al.* (2008) accept to change the axiomatic construction of standard production models to represent particular features of pollution. The first formalisation of that condition comes from Färe *et al.* (1989) who proposed a non-parametric framework aimed to taken into account undesirable outputs using only information about quantities and it is probably the first modern empirical work. After assuming null jointness, they remove the standard assumption of free disposability on whole outputs, arguing that it remains valid only for the subset of desirables. Weak disposability assumption on outputs (y, b) is formalised as follows:

$$(y, b) \in P(x) \text{ and } 0 \leq \alpha \leq 1 \Longrightarrow (\alpha y, \alpha b) \in P(x)$$

Free or strong disposability is valid on a subset of them only if one can reduce their amount without costs:

$$(y, b) \in P(x) \text{ and } (y', b') \leq (y, b) \Longrightarrow (y', b') \in P(x)$$

Free disposability remains valid only for the subset of good outputs:

$$(y, b) \in P(x) \text{ and } y' \leq y \Longrightarrow (y', b) \in P(x)$$

Together these two assumptions lead to different output set as it is graphically showed in figure 1.1 where the region OFBCDE represent production possibilities which are feasible under the assumption of free disposability of all outputs. In symbol one can represent this set as:

$$P_s(x) = \{(y, b) : y \leq Yz, b \leq Bz, Xz \leq x, z \in R^k_+\} \quad (1.4)$$

The weakly disposable counterpart of this set is represented in figure **??** by the area

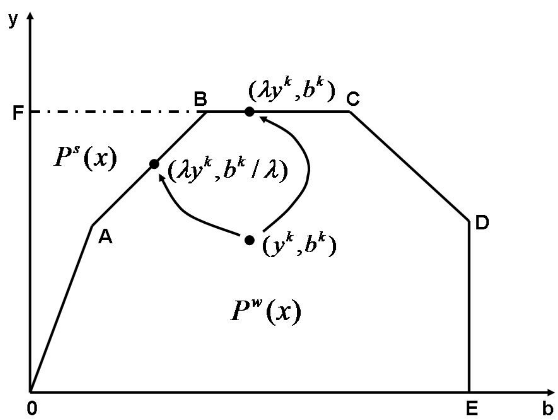

Figure 1.1: Production set under the hypothesis of weak vs strong disposability of outputs and hyperbolic efficiency measure

OABCDE that is formally defined as:

$$P_w(x) = \{(y, b) : y \leq Yz, b = Bz, Xz \leq x, z \in R_+^k\} \tag{1.5}$$

where equality underlines the assumption of weak disposability. Such equality discriminate the different assumption on the subset of undesirable outputs in linear programming problems. How efficiency could change to consider undesirables is the subject of many papers dealing with the regulatory problem. Assuming weak disposability instead of free could be used as a synonymous of binding environmental regulation for the case of pollution. If a law imposes an emission reduction or control, each byproducts become under the attention of decision maker to be limited. Then it is clear that, given inputs, each reduction could only be obtained by dropping good outputs production: if pollutants as outputs cannot be freely reduced, they must be equal to the observed quantity. From that intuition comes the equality constraints in previous linear model.

1.4 Alternative efficiency measures

1.4.1 Hyperbolic efficiency measure

Big step ahead comes with the pursuing of inefficient DMU of an equi-proportional increase and reduction in good and bad outputs, a more complete concept of efficiency that sounds good. Both environmental and economical objective are jointly contemplated and asymmetrically treated: efficiency increases with reduction of undesirables and expansion of desirables. Combining a characterisation of production possibility set meeting previous two assumption Färe *et al.* (1989) propose an hyperbolic concept of efficiency allowing an asymmetrical treatment of weak disposable outputs. Hyperbolic efficiency measure extend classical *DEA* methodology based on radial concept of distance which is firstly applied to normal input-output paradigm. *DEA* models usually generate, for every *DMU*, relative efficiency measures which represent the maximum feasible proportional increase in all output quantities with fixed inputs[3], or in other words the output level reachable if inputs are employed in the best way. In case of hyperbolic productivity, indexes represent how *DMUs* could increase outputs and jointly reduce inputs in the same proportion: that approach leads to an asymmetrical treatment of inputs and outputs. The same idea is extended by Färe *et al.* (1989) to the case of undesirable outputs: resulting efficiency measures credit firms for good outputs increases, inputs reduction and bad outputs contractions. In the case of free disposability assumption the *hyperbolic enhanced efficiency measure* takes the following theoretical form:

$$H_0^s(y^k, b^k, x^k) = \max\{\lambda : (\lambda y^k, \lambda^{-1} b^k) \in P^s(\lambda^{-1} x^k)\} \tag{1.6}$$

where $P^s(\lambda^{-1}x^k)$ represents the production possibility set under assumption of strong disposable outputs when also inputs are jointly reduced of the same amount. Practically hyperbolic productivity indexes could be obtained by solving the following problem, once for each DMU:

$$\begin{aligned} H_0^s(y^k, b^k, x^k) &= \max \lambda \\ \text{s. t.} \quad \lambda y^k &\leq Yz \\ \lambda^{-1} b^k &\leq Bz \\ Xz &\leq \lambda^{-1} x^k \\ z &\in R_+^k \end{aligned} \tag{1.7}$$

The main issues rely in the non linearity of that program, which could be converted in a linear version by assuming some condition to hold for some constraints. Resulting measures of efficiency could be considered as a non-parametric equivalent of Pittman's indexes. If the focus is on outputs, enhanced hyperbolic efficiency measure could take

[3]Or the feasible proportional reduction in all input quantities if the Farrel definition is adopted

the output form, with the name of *conventional hyperbolic outputs efficiency measures* removing conditions on inputs. The weakly disposable version, always in enhanced forms, is very similar, but an equality replace the inequality condition on bad outputs.

$$
\begin{aligned}
H_0^s(y^k, b^k, x^k) &= \max \lambda \\
\text{s. t.} \qquad \lambda y^k &\leq Yz \\
\lambda^{-1} b^k &= Bz \\
Xz &\leq \lambda^{-1} x^k \\
z &\in R_+^k
\end{aligned}
\tag{1.8}
$$

From linear programs is clear the implicit non-linear condition on λ that is imposed to guarantee asymmetric treatment of the two category of outputs. Hernandez-Sancho *et al.* (2000) apply a very similar model to the case of wood producers, partitioning the vector of bad outputs in two parts. Only one of them represents non disposable outputs, the only kind of emissions included among dangerous by regulation. Within the same framework Färe *et al.* (1993) obtained an estimation of pollutants' shadow prices through the exploitation of output distance function properties. More recently Zofio and Prieto (2001) introduce production limits and they analyze manufacturing industries of 14 OECD countries considering only CO2 emissions as bad outputs and Rio's quantitative goals as standards. Ball *et al.* (2004) derive hyperbolic productivity indexes for the case of agricultural outputs, considering as undesirables some byproducts which have a relevant environmental impact in term of human health or aquatic life. Bad outputs are identified in term of pesticide's concentration then as a measure of the risk for humans and animals in the US states. Cuesta and Zofio (2005) introduced a parametric distance function based on a translog form to estimate hyperbolic efficiency measure and they also propose an empirical test of their model. A sample of Spanish saving banks was used and four inputs, three outputs and hyperbolic distance function was used to asymmetrically treat outputs and inputs. Zaim and Taskin (2000) apply an hyperbolic graph measure to estimate environmental performances of OECD countries, considering greenhouse gas emission such CO2. Cuesta *et al.* (2009) estimate both a translog hyperbolic distance function and its deterministic semi-parametric counterpart estimated through linear programming (with some limitations due to normalisation through bad outputs) to compare performances of US power plants. The main advantages of hyperbolic efficiency rely in the possibility to assume different functional firms without limiting the choice to additive items. Estimation strategy is manly pursued in non-deterministic framework, then linearity it is not a key factor.

1.4.2 Slack based measures of efficiency in presence of undesirables

Slack based measures of eco-efficiency have as starting point purely environmental performances to which are added consideration on an inefficient usage of economical resources. Standard EPI ignores the fact that some efficient DMUs are dominated in term of inputs or outputs. The problem of scarce discriminating power and absence of economical considerations, is the solved adding slacks variables for inputs and good outputs. Zhou *et al.* (2006) propose one of the first extension of slack based efficiency score to the case of undesirable outputs. After estimating λ from EPI linear program, economic inefficiency could be detected via the following model:

$$
\begin{aligned}
\rho^* &= \min \frac{1 - 1/N \sum_{n=1}^{N} s_n^- / x_{n0}}{1 - 1/M \sum_{m=1}^{M} s_m^+ / y_{m0}} \\
\text{s. t.} \quad \sum_{k=1}^{K} z_k y_{mk} + s_m^+ &= y_{m0} \\
\sum_{k=1}^{K} z_k x_{nk} + s_n^- &= x_{n0} \\
\sum_{k=1}^{K} z_k u_{jk} &= \lambda^* u_{j0} \\
z &\in R_+^k, \qquad s_n^-, s_m^+ \geq 0
\end{aligned}
\tag{1.9}
$$

Slack variable are used to detect economic inefficiency, then a composite indicator of both economic and environmental performances could be obtained by multiplying ρ^* and λ^*. Sueyoshi and Goto (2011) and Sueyoshi *et al.* (2010) propose a combination of two DEA models formulated using slacks to get a composite frontier able to consider both good and bad outputs. Some problems arise in the identification of efficient firms in the case of contradictory results from the two models run. They propose an application to Japanese electric generating firms and US coal fired firms, where two slack based model are estimated together, unifying good and bad outputs spaces. All efficiency measure proposed are formulated as linear problems using slack formulations, but some of them are not completely linear and the problem of dominated efficient DMUs still remains.

Other application of slack based measure are Lozano and Gutiérrez (2010) who apply the model to airports, considering delays as undesirable effect. Finally Fukuyama and Weber (2009) summarise the main different concepts of slack based inefficiencies used in the literature, including also the directional idea into the model. Slack based and directional distance function models could be considered related: Färe and Grosskopf (2010) shows slack based model could be seen as a particular case of DDF or, anyway, they could restated in a more general way using DDF.

1.4.3 Other method recently applied

Also if some models are proved to be more reliable than other, many applications or basic models' extension are performed in order to deal with some particular issues. Zhou *et al.* (2008) estimates environmental efficiency scores by setting LP very similar to DDF, without an explicit reference to that framework. The main insight is to underline technology's return to scale features by recalling some suggestion from Färe and Grosskopf (2004) where in a DDF framework, VRS are is imposed. In addition, by assuming an increasing factor on good outputs, some imprecision coming from CRS are highlighted and partially solved. Mixed environmental and economical efficiency indexes come from the following non-linear program, that is transformed in a linear form after some passages:

$$
\begin{aligned}
\overrightarrow{D}_0(x^k, y^k, b^k; y^k, -b^k) &= \min \frac{\lambda}{\theta} \\
\text{s.t.} \qquad x^{k'} \geq \sum_{k=1}^{K} z_k x_{kn}, &\quad n = 1, 2..N \\
\theta y^{k'} \leq \sum_{k=1}^{K} z_k y_{km}, &\quad m = 1, 2..M \\
\lambda b^{k'} \leq \sum_{k=1}^{K} z_k b_{kj}, &\quad j = 1, 2...J \\
\sum_{k=1}^{K} z_k = 1 & \\
z_k \geq 0, \theta \geq 0, \alpha \geq 1 &\quad k = 1, 2...K
\end{aligned}
\tag{1.10}
$$

It is estimated by changing the objective function and introducing additional hypothesis, then in a more problematic way in respect to DDF.

1.5 Directional output distance function

1.5.1 Theory and main advantages

This was an important step ahead and still now it is practically the concept more widely applied in recent paper where undesirable are taken into account. Developed from a theoretical perspective in Chambers *et al.* (1996), its properties were explored later in Chambers *et al.* (1998). The concept of directional distance function was so important because is very generic and was able to encompass all previous definition of input and output radial distance functions. It was also useful from a practical point of view because other concept of efficiency allowing an asymmetric treatment of bad outputs, such hyperbolic measures, suffered from non-linear constraints. Färe and Grosskopf (2000) explore many duality correspondence for input and output distance function until the final proof of DDF generality and its property of encompassing the other two less general concepts. While input distance function is the dual counterpart of cost function and output distance function of revenue function, DDF is formulated as the dual counterpart of profit function. In fact the initial idea of directional distance function is in term of input-output and lead to an asymmetrical treatment of input and output, with a immediate recalling of profits. The natural extension to the bad-output problem appears in the first empirical application by Chung *et al.* (1997) where an extension to Malmquist-Luenberger productivity indexes is also provided. In dealing with emissions the more general concept of DDF is limited to directional output distance function (DODF), ignoring inputs side and assuming them as fixed. Formalising concepts:

$$\overrightarrow{D}_0(x, y, b; g_y, g_b) = \max\{\beta : (y, b) + (\beta g_y, \beta g_b) \in P(x)\} \tag{1.11}$$

where $g = (g_y, g_b)$ is the directional vector and $P(x)$ is the output set. In practise directional output distance function re-scale the observed output vector (y, b) on the frontier of the output set following the g direction. The main advantages of that methodology could be summarised in two points:

- Technology is represented in a way that immediately derives from reality, nor negative quantity neither data transformation are necessary for negative output. Each firm produce good and bad output in positive amount, but they are treated asymmetrically in productivity calculations.

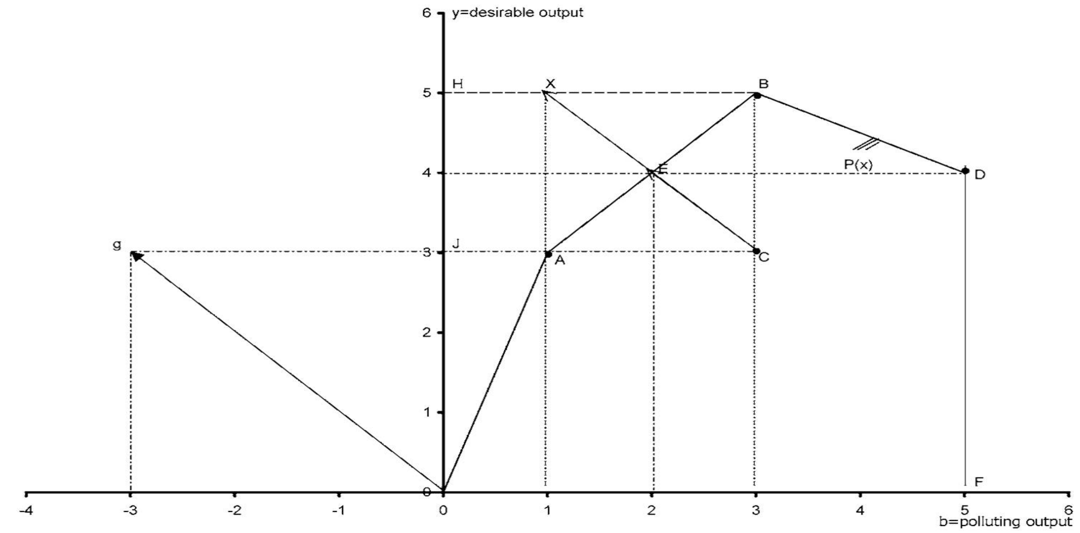

Figure 1.2: Directional distance function, a graphical representation from Domazlicky and Weber (2004)

- Every constraint in the estimation problem could be formulated as linear condition, then is possible to estimate directional distance function using linear programming as in all DEA applications.

In principle each directional vector could be a proper choice, but already in the first theoretical presentation of that function Färe and Grosskopf (2000) suggest to set directional vector equal to observed vector then in this case g become $g = (y, -b)$. Such assumption allow to obtain a measure of inefficiency independent from the amount of outputs with an immediate interpretation as percentage. Directional distance function is null when the output vector cannot be expanded along the g direction. Taking the suggested g the interpretation is as follow: $\overrightarrow{D}_0(x^k, y^k, b^k; y^k, -b^k) = 0$ when firm k is on the frontier or in other words do not exist another firm [4] able to produce less bad outputs and more good outputs at the same time. Figure 1.2 gives a graphical representation of the output possibility set and directional distance function that could be seen as the ratio of two segments in the graph. Considering point C, maximal feasible expansion in the pre-assigned direction is 0.33, given by $\overrightarrow{D}_0^W(x^k, y^k, b^k; y^k, -b^k) = CE/0g$ if weak disposability is assumed. Moreover, when standard assumption of free disposability is valid on the whole set of outputs, $\overrightarrow{D}_0^F(x^k, y^k, b^k; y^k, -b^k) = CX/0g$ takes a value of 0.66 [5]. In general a DDF value greater than zero gives the level of inefficiency and in particular the reduction

[4] Or a linear combination of efficient firms

[5] Data, graphics and values of the example come from Domazlicky and Weber (2004)

of bads and expansion of goods technically feasible. Many directions appear in published paper, but some of them gives results in a non-relative terms and create more difficulties in the interpretation of results. For example Picazo-Tadeo and Prior (2009) apply DDF assuming a directional vector $g = (1, 0)$, considering only expansion of good outputs as productivity driver, but results they get are in output quantities instead of a fraction of them. Whichever direction is selected, empirically one have to solve for each firm a linear program that it is not in standard form as in all classical DEA models. In case of weak disposability the problem become as follow, with an unusual equality among linear constraints suggesting this non-standard hypothesis. The following LP represents the classical case of $g = (y, -b)$:

$$\begin{aligned} \overrightarrow{D}_0(x^k, y^k, b^k; y^k, -b^k) &= \max \beta \\ \text{s. t.} \qquad x^k \geq Xz & \\ (y^k + \beta y^k) &\leq Yz \\ (b^k - \beta b^k) &= Bz \\ z &\in R^k_+ \end{aligned} \tag{1.12}$$

The big majority of all empirical applications are estimated using linear programming, then in deterministic way, where all the detected distance from the frontier is assumed as inefficiency, without statistical noise. This is a limit of this approach, but the absence of any hypothesis on functional form of the technology makes computation free of miss-specification problems. Another issue of fully non-parametric approaches relies in the difficulties to estimates pollutants' shadow prices. When a particular functional form is assumed, the derivation of shadow price is immediate, as the computation of elasticities and other important economic insights such as returns to scale. Some studies more interested in this latter aspects, propose mixed approaches where a specific functional form is assumed, normally an additive quadratic, while the estimation method remain non-stochastic and based on linear programming. Some additional constraints have to be imposed to guarantee appropriate distances computations, Färe *et al.* (2005) remain the best example of that approach. The common choice on additive quadratic form is motivated by its good capacity to be second order approximation of all functions.

Purely stochastic applications are still infrequent, even if a good theoretical background is given by Färe *et al.*(2005). The difficulties to perform this kind of analysis are mainly due to problem of data gathering, it is very uncommon to have big data sets

Table 1.1: Recent application of DDF, 36 papers published in international journals

Autors	Decision Making Units	Country	Level	Estimation	Form
Chung *et al.* (1997)	Pulp and paper mills	Swedish	Firm	Determinstic	None
Weber and Domazlicky (2001)	48 states, manufaturing	US	Aggr.	Determinstic	None
Färe *et al.* (2001)	Manufacturing sectors	US	Aggr.	Determinstic	None
Arocena and W. Price (2002)	Electric generators	Spain	Firm	Determinstic	None
Boyd *et al.* (2002)	Glass manufacturer	US	Firm	Determinstic	None
Lee *et al.* (2002)	Electric generators	Korea	Firm	Determinstic	None
Domalizlicky and Weber (2004)	3-digit chemical industry	US	Aggr.	Determinstic	None
Färe *et al.*(2005)	Electric generators	US	Firm	LP-Parametric	Quadr.
Picazo-Tadeo *et al.* (2005)	Ceramic producers	Spain	Firm	Determinstic	None
Yoruk and Zaim (2005)	OECD countries	OECD	Aggr.	Determinstic	None
Blancard *et al.* (2006)	Agricultural units	France	Firm	Determinstic	None
Färe *et al.*(2006)	Agricultural units	US	Firm	LP-Parametric	Quadr.
Kumar (2006)	46 countries	World	Aggr.	Determinstic	None
Färe *et al.*(2007)	Coal-fired power plants	US	Firm	Determinstic	None
Marklund and Samakovlis (2007)	15 EU countries	EU	Aggr.	Parametric	Quadr.
McMullen and Noh (2007)	Bus transit agency	US	Firm	Determinstic	None
Watanabe and Tanaka (2007)	Provinces	China	Aggr.	Determinstic	None
Lozano and Gutierrez (2008)	28 countries	Kyoto	Aggr.	Determinstic	None
Nakano and Managi (2008)	Electric generators	Japan	Firm	Determinstic	None
Yu *et al.* (2008)	Airports	Taiwan	Firm	Determinstic	None
Barros (2008)	Hydroelectric Generators	Portugal	Firm	Determinstic	None
Kortelainen (2008)	EU members	EU	Aggr.	Determinstic	None
Picazo-Tadeo and Prior (2009)	35 ceramic tile	Spain	Firm	Determinstic	None
Bellenger and Herlihy (2010)	Macroinvertebrates	Pacific Sea	Individ.	LP-Parametric	Quadr.
Fukuyama and Weber (2010)	Japanese Banks	Japan	Firm	Determinstic	None
Kaneko *et al.* (2010)	30 provinces	China	Aggr.	Determinstic	None
Kumar and Madheswaran (2010)	State Cement industry	India	Aggr.	Determinstic	None
Macpherson *et al.* (2010)	US regions	US	Aggr.	Determinstic	None
Oh (2010)	46 countries	World	Aggr.	Determinstic	None
Oh and Hesmati (2010)	26 countries	OECD	Aggr.	Determinstic	None
Simar and Vanhems (2010)	Mutual funds	US	Firm	Determinstic	None
Kumar and Managi (2010)a	Electric generators	US	Firm	LP-Parametric	Quadr.
Kumar and Managi (2010)b	51 countries	World	Aggr.	Determinstic	None
Mahalberg *et al.* (2011)	EU countries	EU	Aggr.	Determinstic	None
Peyrache and Daraio (2011)	Agricultural producers	Italy	Firm	Determinstic	None
Zhang *et al.* (2011)	Regional provinces	China	Aggr.	Determinstic	None

able to collect large number of observations. One of the only stochastic approach to DDF is performed by Marklund and Samakovlis (2007), who propose a comparison between stochastic and deterministic estimates for a quadratic formulation of DDF. They results shows similar conclusion in term of shadow pricing and for the main estimated parameters. Table 1.1 collects all the main applications appeared in international journals which estimates DDF including undesirable outputs. From an initial period of application mainly focused to firm level data, in most recent works aggregate investigation are more numerous. Final picture shows 19 papers analysing individual performances and 17 dealing with aggregate aspects, mainly concentrated in the period 2010-2011. Around the 25% of considered works investigate the US case, but considering micro level articles, this share increase to 40%. The same percentage of individual level papers analyses subject operating in the energy sector such as thermal power plants or hydroelectric generators. All the analysed studies are focused on actors operating in particular sectors and databases are characterised by small numbers of units; as well in the case of aggregate studies for problem of data gathering on environmental side.

1.5.2 Some recent extension and new research directions

Some innovative insights are explored recently in order to extend some limits an to develop new econometric technique on the DDF concept. A Multiplicative extension of DDF is theoretically introduced by Peyrache and Coelli (2009) to overcome scale variant issues in the traditional additive framework of DDF. Given the high discretionary choice of directions, Peyrache and Daraio (2011) propose an empirical tool to verify the sensitivity of efficiency measure to changes in the directional vectors. An application to the Italian agricultural sector demonstrates the procedure validity and represents probably the first attempt to estimate environmental DDF in Italy.

Regarding two stage models, Fukuyama and Weber (2010) apply a network adaptation of the idea of DDF exploiting the possibility to restate directional ideas using directional slacks. They estimates directional-slack based efficiency measure for a group of Japanese banks assuming a two stage model, where deposits are the intermediate outputs produced in the first stage that became an inputs in the production of loans and securities. In all the network formulations bad outputs are included in the model and jointly minimised while desirable are expanded. Finally Simar and Vanhems (2010) propose a first probabilistic formulation of DDF, including part of the econometric theory developed by Simar and Wilson (2007) for the standard DEA. They evidence how standard statistical properties of radial efficiency estimators could be easily extended to the case of DDF. They also propose robust version of DDF introducing order-m and order- α quantile version of these distances.

1.6 Conclusion

This literature review tries to draw a simplified picture of all the most applied methodology to deal with the problem of undesirable outputs in efficiency analysis. Its main goal is to represent the state of art of deterministic efficiency measure for the inclusion of bad outputs. Many models have been proposed in less and more recent papers, but some approaches became more popular than others, mainly for their simplicity of application and for their capacity of represent real production processes. If in previous literature reviews no winners seems to clearly emerge, in the most recent period, directional distance function seems to stand out on other approaches. Its mainly advantages rely in its additive properties which allow to model efficiency problems using linear programming. Moreover the definition of productivity and efficiency is more flexible and this allows to asymmetrically treat different category of outputs, adapting the model to particular features of each situation. Results depend on the particular direction chosen, but some recent developments are trying to clarify sensitivity of outcomes to these choices. Finally this review tries to presents the most recent tools and some new perspectives for the application of DDF in future works.

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Chapter 2

Global efficiency and environmental protection's effects: evidence from Italian polluting industries

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Abstract

The aim of the paper is to extend previous literature on directional distance function (DDF), concentrated on small sample of homogeneous firms producing a limited number of pollutants, to an Italian sample of heterogeneous firms. An high number of pollutants characterised by a wide range of toxicity level have been considered for 5 industrial sectors which are subjected to the same European normative framework. Environmental data comes from highly reliable public sources. Total efficiency is measured by applying the directional distance function model and a proxy of environmental regulation's opportunity cost is derived. Results shows a significant impact of normative constraints in term of potential revenue lost and also an interesting difference in mean environmental performances emerges among industries. Some hypothesis are then tested using modern second stage technique. Economical and financial structure show a significant explanatory power on environmental efficiency and regulatory impact indicators.

JEL classification: D24, Q50, Q52, Q56
Keywords: Directional Distance Function, Environmental efficiency, Second stage Analysis

2.1 Introduction

The attention on environmental protection and sustainability of industrial activities is continuously raising across all over the world. In Europe the attention on green performances of production process is particularly high and environmental regulation, as a consequence, is particularly stringent. Recent introduction and successive modifications of the so called IPPC (Integrated Pollution Prevention and Control) Directive, create a set of obligation becoming more restrictive for firms involving an increasing number of production processes. Many firms are actually forced to measure, control and reduce their emission levels trying to convince institutions that their processes incorporate the so called BAT (Best Available Technique) to limit environmental damages. The common trend to all the developed countries shows a public opinion more and more adverse to polluting industrial sites. Stakeholders and consumers are paying increasing attention on green performance indicators, furthermore entrepreneurs and managers try to adopt eco-efficiency as a strategic choice. The result is a growing demand for scientific research aimed at creating productivity indexes or more generally performance measures which take into account both economical and environmental aspects of firms behaviour. Global productivity indexes were proposed both in non-parametric and parametrich literature since Färe *et al.*(1989) who introduce hyperbolic efficiency measure adding non-linear constraints to standard DEA approach. Scheel (2001) and Zhou *et al.*(2008) summarise the main application using deterministic approach without changing the basic idea of distance used in DEA applications. Literature on parametric approach, solves undesirable outputs by also adding non-linear constraints on output set and estimating parametrically the production frontier (Zofio and Prieto, 2001; Ball *et al.*, 2004; Cuesta and Zofio, 2005). The key problem is an asymmetric treatment of good and bad outputs in order to discredit firms which increase their emissions. The model applied in this paper is based on the concept of Directional Distance Function that Chambers *et al.*(1996) and Chambers *et al.*(1998) propose at theoretical level. The power of that tool is the possibility to modify the direction in which to search for an the efficient counterpart of each firms and this allow to credit firms for reduction in undesirable outputs. DDF is an additive concept, then a standard DEA procedure could be applied and no assumption are needed on the functional forms of technology. Chung *et al.* (1997) applying DDF find significant differences in firm's ranking and estimated inefficiencies when water emission are taken into account analysing paper and pulp mills in US during the 1980s. Boyd *et al.* (2002) analyse data from a small sample of glass US manufacturing firms collected from 1987-1990 and find significant differences in comparison to standard approaches and not negligible losses due to pollution control. Similar results come from more modern applications by McMullen and Noh (2007) on vehicle emissions related to transit buses firms in US where also in this case standard DEA fail in ranking public companies. Färe *et al.* (2007) apply the environmental production function to estimates pollution abatement control costs in coal-fired power plants around 5-17% of physical energy production in 1995. Recently Kumar and Managi (2010)a apply DDF to a sample US thermal power plants, which are included in the Title IV of the 1990 Clean Air Act Amendments. In this case the quasi market instruments (emission permit trading system) are able to stimulate innovation and then a joint reduction of pollutants while electricity production is also raising. Some application of the deterministic DDF concept are also performed at aggregate level, to extend the standard analysis on micro-units, for example Macpherson *et al.* (2010) consider US regions or Kumar and Managi (2010)b country-level comparisons.

Concerning the European case applications are limited, Picazo-Tadeo *et al.* (2005) and Picazo-Tadeo and Prior (2009) analyse the Spanish ceramic industry, both before the new IPPC regulation scheme, finding significant results. Also for tile Spanish firms environmental regulation is significant and a negative correlation between size and regulatory opportunity costs come out from their analysis. In the majority of previous works analysed activities produce more then a limited number of pollutant introduced in the efficiency evaluation, but they are normally ignored, focusing attention on the main substances released. Under the IPPC discipline (directive 1996/61/EC, 2008/1/EC) firms are forced to apply the BAT in order to have allowances to pollute, but if some thresholds on quantity and production capacity are overcome, firms also have the obligation to declare their emissions. A huge number of pollutants different in toxicity have been considered for sectors which are subjected to the same normative framework, but characterised by production process very far one to each other. Data on many substances are available and then here used to have a more complete picture of industrial pollution from each firms. Another key issue comes from the definition of the BAT: they only represent an average environmental practice, moreover only those technique feasible at reasonable costs for both existing and new installations have to be considered. First in class technology are part of the BAT, then it makes sense to estimate a real technical frontier and to compare remaining firms with it. The aim of the paper is, after formulated a theoretically reliable model, to measure efficiency when both desirable and undesirable output are produced. Firms coming from different sectors subject to the same regulatory framework are considered and many pollutants are included as undesirable outputs. An estimation of total regulatory impact is derived by comparing productivity estimates under a regulated and unregulated scenario.

Finally, following the more recent development in efficiency studies, some determinant of observed environmental performance are investigated by applying Simar and Wilson (2007) procedure. By applying an appropriate econometric technique in possible to explain through a regression model efficiency scores and the estimated individual regulatory costs. Only few previous works combine DDF and second stage analysis, among them Nakano and Managi (2008) and Watanabe and Tanaka (2007) focusing on firms while Kumar (2006) on cross country comparisons. The purpose of this paper is to extend previous literature on directional distance function (DDF), concentrated on small sample of homogeneous firms which produce limited number of pollutants, to an Italian sample of heterogeneous firms operating in 5 different manufacturing industry. A totally non-parametric approach is adopted to obtain more reliable estimates free from miss specification problem due to a wrong choice of the functional form. The remainder of this paper is organised as follows: section 2 presents the model, the database and its related issues are shown in section 3 and empirical results are reported in section 4. This analysis is briefly concluded in section 5.

2.2 Modelling environmental performance: a directional distance function approach

To model production process when pollutants are jointly produced with good outputs the directional output distance function by Chambers *et al.* (1996) is applied here. Let $x = (x_1, ..., x_N) \in R_+^N$ be a vector of inputs, $y = (y_1, ..., y_M) \in R_+^M$ a vector of good outputs and $b = (b_1, ..., b_J) \in R_+^J$ a vector of bad outputs such as pollutions. The output set $P(x)$ consists of combinations of good and bad outputs that could be produced using an input vector x.

$$P(x) = \{(y, b) : x \quad \text{can produce} \quad (y, b)\}, x \in R_+^N$$

. Färe *et al.* (2007) some standard axioms are satisfied by environmental technology.

1. *Inactivity*. The choice of remaining inactive is always possible from a technological point of view. Then $0 \in P(x), \forall x \in R_+^N$, but of course seems to be unrealistic especially in polluting industries where the big amount of investment is typical.

2. *Compactness*. $P(x)$ is compact (a finite input mix x gives finite results on output space (y, b))

3. *Free disposability of inputs.* Under classical technological regime, an increasing quantity of inputs could always produce a fix quantity of outputs. Inputs are then freely disposable $P(x) \subseteq P(x')$ if $x' \geq x$, or in other words, from a technical viewpoint, firms can choose to produce the same amount of outputs by consuming more inputs. This assumption in the field of environmental sensitive production is strong as Macpherson *et al.* (2010) underline, because input consumption and pollution may be in same way related.

Starting from these classical assumptions on the technology and input-output sets, which are always valid when an efficiency analysis is performed, in presence of undesirable outputs one have to consider the fact that pollution is jointly produced with good outputs as a sort of byproduct results and that reducing it is costly as Färe *et al.* (1989) underline. Two additional environmental axioms are then added to the standard framework:

4. *Null jointness.* It is impossible to observe positive amount of good outputs without pollution, or in formulae $(y, b) \in P(x)$ and $b = 0 \Longrightarrow y = 0$

5. *Weak disposability assumption on outputs.* Each couple of vectors (y, b) is assumed to be weakly disposable, then they cannot be freely reduced:

$$(y, b) \in P(x) \text{ and } 0 \leq \alpha \leq 1 \Longrightarrow (\alpha y, \alpha b) \in P(x)$$

In words only proportional contraction of both good and bad outputs are feasible, because the decrease on bad outputs could only be performed by reducing desirable outputs or increasing inputs. It is commonly accepted that weak disposability proxy behavioural limitation of a firm in a regulated environment. Free disposability remain valid only for the subset of good outputs for which every reduction is still technically feasible without costs.

$$(y, b) \in P(x) \text{ and } y' \leq y \Longrightarrow (y', b) \in P(x)$$

If there are no environmental regulation that forced firms to control and reduce pollution one could costless dispose of bad outputs. In this case previous limitation on the outputs sets are rejected and free disposability became valid on all outputs $(y, b) \in P(x)$ and $(y', b') \leq (y, b) \Longrightarrow (y', b') \in P(x)$.

The directional output distance function (DODF), defined on the output set that meets previous axioms, gives the maximum feasible expansion of outputs in a pre-assigned direction maintaining inputs unchanged. An appropriate direction should be choose in order to guarantee an asymmetrical treatment of desirable and undesirable outputs. DODF is defined on $P(x)$, takes a value equal to 0 for efficient firms which contribute to the frontier identification and increase with inefficiency. Theoretical properties and duality correspondences are explored in Färe and Grosskopf (2000) under the initial idea of directional distance function in term of input-output which lead to an asymmetrical treatment of input and output. The natural extension to the bad-outputs problem appeared immediately in the first empirical application by Chung *et al.* (1997). Formally the DODF is defined as follows:

$$\overrightarrow{D}_0^W(x, y, b; g_y, g_b) = \max\{\beta : (y, b) + (\beta g_y, \beta g_b) \in P(x)\}$$

where $g = (g_y, g_b)$ is the directional vector and $g_y \in R_+^M$, $g_b \in R_+^J$. The production possibility set $P(x)$ could be estimated via DEA by solving, for each firm, the following linear problem after fixing a particular directional vector. The trade-off between desirable and undesirable outputs have to emerge in the choice of the directional vector. In the European case environmental regulation imposes a pollution's contraction by adopting the Best Available Technique on the market. From an economical point of view managers are interested in maximise good outputs production, then what emerge is that DMUs want to increase good outputs by contemporary reducing emissions. Following this idea and what is done in many applications the vector $g = (y, -b)$ is chosen with the aim of giving an immediate meaning to β as Färe and Grosskopf (2000) recommend.

$$\begin{aligned}
\overrightarrow{D}_0^W(x^{k'}, y^{k'}, b^{k'}; y^{k'}, -b^{k'}) &= \max \beta \\
\text{s. t.} \qquad x^{k'} &\geq \sum_{k=1}^{K} z_k x_{kn}, \quad n = 1, 2 \\
(1+\beta) y^{k'} &\leq \sum_{k=1}^{K} z_k y_{km}, \quad m = 1 \\
(1-\beta) b^{k'} &= \sum_{k=1}^{K} z_k b_{kj}, \quad j = 1, 2 \\
\sum_{k=1}^{K} z_k &= 1 \\
z_k &\geq 0
\end{aligned} \tag{2.1}$$

Return to scale are assumed to be non constant and the second last constraint is added to the standard CRS formulation. Following Fukuyama (2003) this assumption seems reasonable and allows to focus attention on inefficiencies under the control of managers, excluding scale inefficiencies.

2.2.1 Regulatory impact

Färe *et al.* (1989) suggest that by removing weak disposability assumption is possible to simulate an hypothetical unregulated frontiers. In many recent papers investigating environmental efficiency, such as Picazo-Tadeo *et al.* (2005), Färe *et al.* (2007) or Picazo-Tadeo and Prior (2009) is possible to find estimation of total regulatory impact by comparing efficiency score of firms in regulated and unregulated framework. In doing this it is necessary to estimate another model that extend free disposability to all outputs. Linear problems remain as in previous case, but the last equality is replaced by an inequality with an unchanged directional vector.

$$
\begin{aligned}
\overrightarrow{D}_0^F(x^{k'}, y^{k'}, b^{k'}; y^{k'}, -b^{k'}) &= \max \beta \\
\text{s. t.} \qquad x^{k'} &\geq \sum_{k=1}^{K} z_k x_{kn}, \quad n = 1, 2 \\
(1+\beta) y^{k'} &\leq \sum_{k=1}^{K} z_k y_{km}, \quad m = 1 \\
(1-\beta) b^{k'} &\leq \sum_{k=1}^{K} z_k b_{kj}, \quad j = 1, 2 \\
z_k \geq 0, \sum_{k=1}^{K} z_k &= 1
\end{aligned}
$$

In words it is possible to decrease bads without cost: this is equivalent to say that regulation does not exist any more, and by comparing this two sets of results is possible to create a proxy of the potential good output loss due to regulation. As Domazlicky and Weber (2004) suggest with $g = (y, -b)$ directional vector, a reliable indicator of regulatory impact (RI) take the following form:

$$
RI = \overrightarrow{D}_0^F(x^{k'}, y^{k'}, b^{k'}; y^{k'}, -b^{k'}) - \overrightarrow{D}_0^W(x^{k'}, y^{k'}, b^{k'}; y^{k'}, -b^{k'}) \tag{2.2}
$$

This indicator can only give a partial proxy of the total cost imposed by environmental regulation, as Zofio and Prieto (2001) underline that methodology measure exactly total regulatory impact if and only if no regulation exist before: if in some way firms are already forced to consider pollution it is not possible to identify the real free disposable frontier. All the invisible cost, undertaken throughout the years to comply with previous law and pollution standard, could not be measured and also the potential output loss cannot be derived. What is measurable is the visible departure from actual best practice frontier in the case of weak disposability to an hypothetical free disposable one that is dependent from all previous choices taken under environmental constraints. Bearing that limitation in mind and using a sort of simulated reality, combining results by both set of linear problems it is possible to create a proxy of regulatory impact in term of potential good output lost. The same theoretical framework on second stage analysis described in previous section also apply to the case of RI. DGP process is very similar to that described for efficiency estimate and also in this case a zero value of RI represents a feature of estimation. It's very hard to sustain that removing environmental constraints does not have impact on good output production.

2.2.2 Second stage analysis

The general aim of the paper is to understand the presence of a specific industry effect that represent pure technical differences and costs related to the implementation of environmental protection. The effect of external and internal variables which could influence environmental efficiency has to be isolated, focusing on those variables that are not under the direct control of manager, such as long term choices. This approach is normally investigated in classical DEA models, but in DDF framework a second stage analysis is not jet a common practice. Daraio and Simar (2008) listed directional distance function among the extension of classical DEA models which inherit the same statistical properties of standard DEA scores. Some previous works on DDF apply a second stage model, but based on Tobit model for censored data like Watanabe and Tanaka (2007) or Blancard *et al.* (2006). Only Picazo-Tadeo *et al.* (2011) perform estimates based on the recent results by Simar and Wilson (2007) to the case of DDF efficiency scores. According to their seminal work, classical estimation method based censored model, could lead to misleading conclusion: a truncated regression is strictly preferred in order to exclude from second step efficient DMUs which drive the unknown technological frontier. Following

Picazo-Tadeo *et al.* (2011), we assume the following simple regression model:

$$\hat{EE_k} = w_k\gamma + \varepsilon_k, \quad k = 1, ...K \tag{2.3}$$

where w_k represent a set of variable which potentially affect environmental performances. The unknown efficiency scores EE_k, based on an unknown technological frontier, are estimated according to the DODF framework by $\hat{EE_k}$ during a first stage based on section 2.2.1. The only difference from second stage in standard DEA approach is the truncation point. In the original version by Simar and Wilson (2007) efficiency scores are bounded by unity, here, under DODF, they are lower bounded by zero. The assumption on ε_k remain the same before truncation, normal distribution with zero mean and unknown variance. What change is the truncation point derived by the new condition $\varepsilon_k \geq -w_k\hat{\gamma}$[1]. The econometric model is then estimated via maximum likelihood technique applying a truncated regression model. In order to obtain a more reliable inference confidence interval are derive assuming a non standard distribution of coefficient. A bootstrap procedure is performed on the base of the steps proposed by Simar and Wilson (2007) for their Algoritm 1. The sequence of actions follows Latruffe *et al.* (2008), but the reference work is Simar and Wilson (2007), where all steps are more formally treated:

1. The application of a truncated regression model allow to estimate, via maximum likelihood, a first set of coefficient $\hat{\gamma}$ and a first estimate of the variance of error term $\hat{\sigma}_\varepsilon$.

Then looping over S times the next three steps gives a set of estimates for each coefficient $\hat{\gamma}$ and for $\hat{\sigma}_\varepsilon$.

2. A casual extraction for ε_k from a normal distribution is drawn:

$$N(0, \hat{\sigma}_\varepsilon^2), \text{ left truncated at the point } (-w_k\hat{\gamma}) \tag{2.4}$$

   and we repeat these procedure for each inefficient observation on efficiency score.

3. The computed environmental efficiency score are corrected for the potential bias by adding the casual extraction ε_k to each inefficient term predicted by the truncated regression model.

$$EE_k^* = w_k\hat{\gamma} + \varepsilon_k \tag{2.5}$$

[1]In the analysis the second stage is also performed on standard DEA efficiency score. In this case the truncation point follows standard formulation and the condition became $\varepsilon_k \geq 1 - w_k\hat{\gamma}$

4. Using maximum likelihood the truncated regression of these new variable is estimated on the original explanatory variable included in the first model. By repeating S times the previous this 3 steps a set of bootstrap estimates is obtained from the sample:
$$G = [(\hat{\gamma}^{*}, \hat{\sigma}^{*}_{\varepsilon})_g]_{g=1}^{S} \tag{2.6}$$

5. Finally using the bootstrap values in G to construct new confidence intervals around estimated parameter $\hat{\gamma}$ and $\hat{\sigma}_{\varepsilon}$ coming from the first truncated regression, allow to get a more robust and reliable inference.

2.3 Data

2.3.1 Inputs and outputs data

Environmental data comes from the European Pollution Release and Transfer Register (E-PRTR), a public register published on-line by the European Environment Agency (EEA). This steps is part of the so called *third wave* of environmental regulation(Cañon-de-Francia *et al.* 2008) that is based on information disclosure. An European Pollution and Emission register is introduced with directive 1996/61/EC, but it became real only after 2000; with the regulation 166/2006 EC its application has been enlarged and also transfer activity is traced. E-PRTR is relatively young in comparison with US the Toxic Release Inventory born in 1986 and then it is still less investigated. All firms operating in 9 particular sectors must declare emissions if a double thresholds, on production capacity and emissions level, is overcome. General information, release means (air, water or soil), methods of measurement, particular installation and emission quantities must be declared. The level of information is very fine: data must be delivered for each plant and for each of 91 chemicals that are listed in the directive. I consider in my analysis only strictly manufacturing industries, excluding sectors with peculiar characteristics or for which data are scarce. A short overview of sectors considered and excluded is given in table 2.1.

Only emissions in air and water are used in my analysis because soil and water means of release are often overlapped and data on soil emission always missed. Economical data come from AIDA database, by Bureau Van Djick, that collects balance-sheets of Italian firms which are forced to lay their accounts. Both economical and environmental variables are relative to 2007. In absence of physical data on production and given the heterogeneity of sectors included in the analysis an economic measure of good outputs is used. Among

Table 2.1: E-PRTR industries

Analysed sectors	Excluded sectors
2. Production and processing of metals	1. Energy sector
3. Mineral industry	5. Waste and wastewater management
4. Chemical industry	7. Intensive livestock and aquaculture
6. Paper and wood	8. Animal and vegetable products
9. Other activities	

balance sheet variable, following Pieri and Zaniotto (2010), total production value (Y) is represented by the total turnover, net of inventory changes. Capital stock (K) is measured as the net value of tangible fixed asset included and Labour (L) is proxied by the total labour costs, trying to take into account quantity and quality of human resources. Intermediate goods (M) are also included as an input of the production process; their value is obtained by the sum of raw material costs (net to inventory change) and costs of services. All data on inputs and good outputs are expressed in Euros. It is important to notice that all balance sheet data only represent proxies of real variable and then estimates cannot be precise. DEA models are created to work with physical quantities and to compare homogeneous production process, here monetary values are used to obtain comparable input and output measure among sectors, results have to be carefully interpreted. In matching environmental and economical data, emissions by different production plants have to be integrated on release means and on firm. Data remain untreatable from a linear programming point of view: some substances are characteristic of specific sectors, but the main point was the impossibility to estimate DODF without some aggregation of variables[2]. All information on chemical emission are condensated by weighting for the dangerousness of each substances. An aggregation method based on the idea of damage function, as it is suggested by Färe *et al.* (2007), is adopted here. Firms in E-PRTR are assumed not producing anymore a physical quantity of pollution, but they are creating an environmental damage that imply an impact on public health. This impact is derived as a weighted sum of pollution quantities distinguishing by release mean: each firm's production process has

[2]The 91 chemicals are observed twice, in air and water, for each sector the number of firms never exceed 50.

an air and water environmental impact. Weights are directly derived from E-PRTR regulation, assuming the inverse of allowed thresholds as an indicator of toxicity level on the basis of a similar procedure adopted by Cañon-de-Francia *et al.* (2008). The underlying idea is that an higher threshold indicate a lower toxicity level, then a smaller inverse to weight the related emission produced. In notation:

$$b_{jk} = \sum_{g=1}^{91} d_g q_{kg}, \qquad j = 1, 2$$

where $d_g = \frac{1}{T_g}$, g indexes pollutants, k indexes firms, T represents thresholds relative to each pollutant and q is the total quantity released. The approach is similar to Färe *et al.* (2006), where two human risk-adjusted indexes if pesticide leaching and runoff are used as bad outputs to be minimised in a semiparametric model. Table 2.2 reports, by activity code, inputs and outputs for all the 180 firms data allows to compute DODF. Air and water environmental impacts give some hint on the kind of production process involved: metal and chemical industries are the most polluting, air emission characterise mineral plants and waste-waters paper producers. The last activity code groups some different kind of less polluting process and it's more difficult to characterise the type of prevalent release mean.

2.3.2 Variables affecting eco-inefficiency

In the second stage phase the influence of some possible determinants of environmental and standard efficiency score are investigated estimating a regression model based on modern econometric advances. A complete list of the variables included to test for their explanatory power on the computed level of efficiency level and regulatory costs is here provided. In the majority of the cases balance sheet data are used to create structural indicators, with the idea that a variable could be used as explanatory if decision maker, then managers, cannot influence it in the time period considered (Lovell, 1993). A less stringent interpretation of this concept allow to include some of explanatory variable that could be affected by manager's action in each time period, but given their long run nature, cannot be strongly influenced in the short run.

- *Activity.* Some previous studies, especially performed by specific industrial association, argue that the impact of environmental regulation is higher in particular sector. Maglia and Sasson (2000) underline high costs paid by the European chemi-

Table 2.2: Summary statistics by E-PRTR's activity code, *means and (standard deviation)*

	Eper Activity Code				
	2	3	4	6	9
Inputs (1,000,000s)					
Assets	159.98	77.78	56.81	121.86	116.61
	(371.44)	(86.58)	(137.83)	(251.48)	(396.72)
Labour	59.17	25.81	30.3	32.17	55.21
	(115.22)	(26.94)	(56.21)	(43.84)	(189.64)
Intermediate	568.48	105.58	257.83	236.28	883.99
Goods	(898.27)	(101.75)	(777.42)	(428.6)	(3791.31)
Desirable outputs(1,000,000s)					
Total	730.42	165.29	324.62	293.34	988.94
Production	(1153.23)	(164.81)	(869.57)	(487.14)	(4162.53)
Undesirable Outputs (Impact indicators)					
Air	74.68	20.12	156.29	5.04	28.08
	(272.39)	(32.53)	(440.54)	(11.62)	(123.72)
Water	47.77	0.07	80.37	16.86	20.55
	(185.26)	(0.41)	(325.83)	(37.95)	(102.87)
N	51	36	49	17	27

cal industry compared to US and to other sectors. E-PRTR activity code seems to be accurate and characterised by an high level of correspondence with Italian ATECO codes which are more accurate only in the case of the Chemical sector (E-PRTR code 4) in which are grouped 2 different stream of activity: Pure Chemical industry and Base Pharmaceutical. The underlining idea is that also after controlling for firms' characteristics that are peculiar for each sector and significantly affect environmental performances, some differences remain among industry: this will represent the intrinsic difference among production process in complying with the same normative. Then when policy makers decide to cut environmental impacts of economical activity some sectors will suffer more from their decision and this is due to the intrinsic properties of technology. Dummies for each activity are included and the heterogeneous field of E-PRTR code 9 is assumed as control group.

- *Geographical location*. Firms located in the South of Italy are hypnotised to be less constrained by both formal and "informal" regulation. Secondly the implementation of IPPC and data gathering of E-PRTR is delegated to each regional government which is the competent authority at controlling for preventive authorisation to pollute and for the adoption of Best Available Technique. Different institutional approach and civic sensibility create a different level of pressure on firms in pursuing better environmental performances. Of course also general economical aspects influence overall productivity, then a dicotomic variable (NORD), that take a value of 1 in case of firm located in the Northern Italy, is created and included in estimates.

- *Technological status*. Internal production or external acquisition of technology are considered as a potential factor positively influence efficiency and reducing compliance costs. The dummy TECHNOLOGY takes a value of 1 if firms are involved in significant processes of research and development. The word significant is here used as a synonym of capitalised, then such expenses are listed among assets. This will proxy internal technology creation. The dummy is also equal to 1 if I observe patents buying or other kind of licencing expenses: in this case emerges an external acquisition of technology.

- *Size*. Many studies on productivity consider the relationship between firm's size and performances (Latruffe *et al.*, 2008), also in the field of environmental efficiency size is a potential explanatory variable. In this studies the control for size allows to identify a cleaner industry effect, excluding the different distribution of

SMEs and big firms among industry. What is expected is that large firms could try to improve their corporate environmental performances in order to obtain an high return in terms of image and relation with society. This is particularly important in polluting industry on which public opinion is always diffident. SIZE is measured as the natural log of total production value, also known as asset to turnover ratio.

- *Industrial structure*. Also if the current analysis is focused on the more traditional manufacturing sectors, many differences remain at a structural level among firms producing so different goods. The level of investment appears to be broadly heterogeneous, then it is important to include a variable the turnover generated by each unit of technical investment. A variable STRUCTURE using the ratio total production over tangible assets, similarly to Rose *et al.* (2004). They imply sales over assets to explain environmental performances of S&P500 firms, finding a significant negative relation with emission levels that suggest higher pollution level for higher capital endowment.

- *Self financing capacity*. Nickell *et al.* (1997) include financial pressure as one of the potential contributor to firms performances in a standard analysis of productivity. The self-financing capacity is an important aspect that have to be considered: a firm that highly depends to external sources is less free to invest resources on environmental protection. Banks are more careful about the capacity of re-funds loans than about the attention to environment. In the case environmental efficiency an highly detrimental effect of financial diseases is expected on green choices. An index of financial independence (SELF FINANCE) has been calculate for each k-th firms:
$$SELFFINANCE = \frac{K_k + IK_k}{NW_k + RF_+ TFR_k}$$
where K_k is total of fixed assets, IK_k represents intangible assets, NW_k is the Net wealth, RF summarise Total provision for risk and TFR_k is the total several pay found.

2.4 Results

2.4.1 Environmental efficiency and regulatory impact: description and evidence

For each firms in E-PRTR with complete environmental data, environmental efficiency score are calculated by solving linear program previously showed. All programs are written and solved using R. Before interpreting results it should be underlined that efficiency is a relative concept and then what we get from estimation is the position of each firm in respect to the best of the sample observed for each analysed sector. Five separate frontiers are estimated on five output sets, this allow to assume an homogeneous production process for each subsample. Also if inputs and outputs are designed in a way allowing direct comparison among industries a conservative approach is adopted: the DDF models is estimated separately for each sector. This allow to be more confident about obtained results: for example each chemical firm is only compared with the best in the sample of chemical firms and the same for all other industry. Obtained efficiency results should be robust to structural differences among sectors and they can be directly compared. Table 2.3 shows results from a regulated model, where weak disposability is assumed on bad outputs in comparison to an unregulated framework where undesirable outputs are considered as freely disposable. The value of the estimated distance function β represent the potential contemporaneous increase of turnover and reduction of environmental impact coming from the adoption of the real best technology in all the sample. Second column reports small values, suggesting a good level of environmental performances in all the analysed sectors. The average estimated β is around 4% for all the sample; the poorer performance is reached in Chemicals ($\beta = 6.8\%$) and in Minerals ($\beta = 4.3\%$). Less inefficiencies emerge in Paper and Other activity. Given the fact that each firms have to adopt BAT in order to operate on the market, the estimated DDF could also be interpreted as the distance between BAT technology and First in Class technology in each input-output mix. Adopting this view is easier to interpret results from Paper and Other activities: both sectors are heavily regulated by tradition with a constant increase in standard which firms to adopt an high technological level to reduce pollution. New IPPC rules simply recognise the current situation by assuming the already adopted best technology as BAT.

In table 2.4 results by dimensional class are shown on the basis of European classification. Small and medium enterprises seem to perform better then large firms, but the evidence is more stronger for very large firms which show higher efficiency score under

Table 2.3: Efficiency score by industry, under regulated and unregulated scenario

Activity	$\overrightarrow{D}^W(y,-b)$		$\overrightarrow{D}^F(y,-b)$	
	β	$Pr(\beta=0)$	β	$Pr(\beta=0)$
2.Metals	0.033	70.6%	0.092	37.3%
3.Minerals	0.043	61.1%	0.082	41.7%
4.Chemicals	0.068	57.1%	0.135	32.7%
6.Paper	0.005	88.2%	0.023	64.7%
9.Other	0.009	74.1%	0.040	55.6%
Total	0.038	67.2%	0.087	42.2%

Note: 2.Production and processing of metals, 3.Mineral industry
4.Chemical industry, 6.Paper and wood, 9.Other activities

both regulated and unregulated scenario. Also in the case of dimension, non parametric tests confirm first impression. Krusksal-Wallis procedure, based on ranks, does not allow to accept equality of medians and distributions. Small firms show an unexpected good environmental performance, mainly due to their smaller level of pollution in comparison to large firms. In fact this advantage disappears in the unregulated scenario to confirm emission-related interpretation.

Table 2.4: Results by dimensional class(European Classification)

Activity	$\overrightarrow{D}^W(y,-b)$		$\overrightarrow{D}^F(y,-b)$		RI
	β	$Pr(\beta=0)$	β	$Pr(\beta=0)$	
SME	0.022	75.5%	0.090	47.2%	0.067
Large	0.055	57.3%	0.106	34.4%	0.051
Very Large	0.014	83.9%	0.026	58.1%	0.011

SME: revenues under 50 mlns, Large: revenues between 50
and 500 mlns, Very Large: revenues over 500 mlns

Taking the difference of estimated score in the two previous model leads to a proxy of E-PRTR application or, from a broader point of view, of IPPC framework that impose the adoption of the current BAT. Picazo-Tadeo and Prior (2009) show an effect of 25% in term of total turnover in the Spanish ceramic industry due to the application of IPPC directive after 2007, but intermediate inputs are measured in physical quantities and some aspects are ignored such as services costs. Last column in table 2.4 shows an interesting point already underlined in previous literature, in particular by Picazo-Tadeo *et al.* (2005), of a negative correlation between size and potential good output loss due to regulation. Multiplying RI indicators for the specific production volume of each firm, a proxy of the monetary cost imposed could be obtained and table 2.5 summarise results by industrial sector. Environmental protection seems to have an higher impact in Chemicals and Metals, where its cost is estimated around 6.6 % and 5.9% of the total turnover. The less affected sectors are Paper and Other activities for which previous considerations are still valid and results underline how the estimated RI only take into account departure from an hypothetical and actual free disposable frontier. Mean values of RI indicators differ significantly as non-parametric tests suggest also for the case of sectors. Interaction of size, activity and other individual characteristics also increase the interest on a semi-parametric second stage analysis of results.

Table 2.5: Regulatory Impact and potential output lost

Activity	RI	$Pr(RI = 0)$	Y Lost (mln)	Max Lost (mln)
2.Metals	0.059	37.3%	16.7	209.9
3.Minerals	0.039	50.0%	6.1	37.8
4.Chemicals	0.066	34.7%	5.8	43.5
6.Paper	0.019	76.5%	2.2	29.0
9.Other	0.031	63.0%	1.4	10.0
Total	0.049	46.7%	7.9	209.9

2.4.2 Second stage estimates: net sector effect and other determinants

Previous section shows how efficiency scores are distributed according to activity and firm's size, but controlling for individual characteristics is an essential step to estimate the net effect of technological differences. Firstly mean dimension of firms differ across sectors, but also geographical differences, technology adoption and financial independence appear as good candidate to explain productivity and compliance costs. Thanks to most recent development in econometric theory described in section 3.3 to analyse efficiency indexes, one could estimate a regression model to control and test for a set of potential explanatory variable which jointly affect performances. Following the approach by Blancard *et al.* (2006) where DODF results are maintained bounded below by zero, all the analysis is performed only on inefficient observations ($\beta > 0$). The truncation of inefficiency scores reduce the sample and this cause a problem of dimensionality, that is stronger in the case of weak disposability. This procedure is in line with Simar and Wilson (2007) and it is applied to the first two regression reported in table 2.6. The third reported model explain observed regulatory costs, is performed on the total sample, with the idea that an observation equal to zero is more coherent with reality and not direct results of a limited sample. Negative sign on coefficient indicates reduction of inefficiencies or costs. Confidence interval are computed assuming non-standard distribution of coefficients. The bootstrap procedure described in section 3.3 allows to derive upper and lower bound of the bootstrap confidence interval an this values are reported for each estimated coefficient and for each model. Picazo-Tadeo and Garca-Reche (2007), in analysing productivity in Spanish tile industry, open the possibility to test several hypothesis in the field of directional distance function model. On this basis some hypothesis are tested, verifying the explanatory power of several variables which are previously listed and described. The sample of heterogeneous firms comes from different industry where the same normative framework is enforced and where emissions are measured according to the same rule. An interesting point is to understand how the same regulation apply differently among firms by different sectors after controlling for individual characteristics. If some differences arise among sectors, this partially confirms intrinsic difficulties in reducing or fighting emission which are higher in some sectors. The underling hypothesis of heterogeneity is confirmed in case of significant sectoral dummies, the signs of dummies give the direction in respect to the control group of other activity (E-PRTR code 9). The fact that a separate frontier is run for each industry must be remarked: after controlling for other individual characteristics, more environmental inefficiencies remain in the most polluting sectors. In particular the highest coefficient is observable for Pharmaceuticals

Several interesting points come out from the econometric analysis. First of all sectoral dummies are all significant in model 1 and 2, then differences emerge in respect to the industrial activity and inefficiencies. Firms operating in the pharmaceutical field seem to be less efficient than other firms as underlined by the biggest coefficient, also in the metallurgy and chemicals are possible good efficiency recovery if best practice will be exploited. Less differences seem arising for the regulatory impact estimated: only in the case of metallurgy and chemicals the potential loss of good output observed is statistically in respect to other sectors. Only in the case of global and technical efficiency one can observe real differences among industries, but the regulatory burden seems to be equally distributed across industries if one exclude chemicals and metals. In this two sectors the impact of IPPC principles and the adoption of the BAT seems to have a stronger negative effect on turnover. Firms located in the Northern Italy show a better environmental performance than their counterpart sited elsewhere. The outcome confirms the idea that some

Table 2.6: Second stage truncated regression, coefficient and (bootstrap confidence interval)

	Dependent variables		
Explanatory variables	$\overrightarrow{D}^W(y,-b)$	$\overrightarrow{D}^F(y,-b)$	RI
Metallurgy	**0.297**	**0.189**	**0.043**
	(0.223 ; 0.335)	**(0.132 ; 0.226)**	**(0.012 ; 0.075)**
Minerals	**0.188**	**0.055**	-0.002
	(0.123 ; 0.229)	**(0.01 ; 0.1)**	(-0.034 ; 0.031)
Chemicals (20)	**0.298**	**0.184**	**0.036**
	(0.228 ; 0.329)	**(0.127 ; 0.216)**	**(0.003 ; 0.07)**
Base Pharmaceuticals (21)	**0.38**	**0.181**	0.015
	(0.293 ; 0.424)	**(0.114 ; 0.23)**	(-0.035 ; 0.06)
Paper	0.022	**-0.161**	-0.014
	(-0.063 ; 0.126)	**(-0.208 ; -0.077)**	(-0.054 ; 0.028)
NORD	**-0.071**	-0.031	0.017
	(-0.105 ; -0.03)	(-0.06 ; 0.002)	(-0.008 ; 0.039)
TECHNOLOGY	**-0.092**	**-0.051**	0.003
	(-0.124 ; -0.052)	**(-0.078 ; -0.018)**	(-0.02 ; 0.024)
SIZE	**-0.023**	**-0.06**	**-0.015**
	(-0.038 ; -0.005)	**(-0.07 ; -0.044)**	**(-0.022 ; -0.008)**
STRUCTURE	**-0.016**	**-0.019**	-0.002
	(-0.021 ; -0.009)	**(-0.021 ; -0.013)**	(-0.003 ; 0)
SELF COVERAGE	0.003	**-0.032**	**-0.015**
	(-0.018 ; 0.025)	**(-0.046 ; -0.009)**	**(-0.027 ; -0.002)**
CONSTANT	0.126	0.45	0.123
	(0.114 ; 0.281)	(0.436 ; 0.582)	(0.073 ; 0.167)
SIGMA	0.091	0.117	0.068
	(0.041 ; 0.066)	(0.053 ; 0.073)	(0.06 ; 0.075)
N	59	101	176

Significant variable at 95% are marked in bold authority could be more diligent in requiring the application of BAT and this is probably due to a weaker informal pressure on firms (Cole *et al.*, 2005). In poorer areas, such as the South of Italy, the population has less working opportunities and a lower attention to the environment is tolerated. The disadvantage in term of efficiency disappear when emissions are excluded by the analysis and also regulatory cost seems stable, then worse green performances are not associated with lower compliance costs. The significant effect of size is confirmed and is robust to the control for other individual characteristics. The negative relation between regulatory costs and firms' dimension showed by Picazo-Tadeo *et al.* (2005) also emerges in this context, as a confirmation of the SMEs' difficulties to deal with complicated environmental rule. Larger firms are also able to reach higher performances both environmental and technical, then scale economy seems to overcome extra-emissions due to big industrial installations. Technological investments are negatively related to inefficiencies and this confirms a priori idea, but they are not determinant in the control of regulatory costs. The advantages by the removal of environmental protection are not higher for those firms which invest resources in research or licence buying. Of course current analysis miss big information on research and development because only capitalised expenses are considered. Other individual variables influence efficiency results and in particular industry characterised by a smaller capital endowment seems more inefficient as previous literature suggests. The hypothesis on self-financing capacity is partially negated by empirical evidence because the variable SELF-COVERAGE is not significant nor negative in the model 1 where environmental efficiency is regressed. The financial independence only positively affect technical efficiency and negatively regulatory costs. Firms with a robust financial structure show higher technical performance and are able to pay less cost due to regulation. This is probably due to their capacity to pursue environmental friendly strategy without external interference. Results obtained in table 2.6 should be interpreted with care: the limited sample size and the Simar-Wilson procedure, based on the exclusion of efficient observations, create some dimensionality problems, especially for the model 1.

2.5 Conclusion

This paper examines the relationship between technical efficiency and the pollutants production in some Italian industries where environmental regulation is more pervasive. A classic deterministic directional distance function approach is extended to multiple bad outputs and an emissions aggregation procedure is proposed in order to optimise computations. Differently by other works in the present analysis a lot of pollutants are considered and two different total emissions indexes are created considering dangerousness of each substance and release means. This paper also faces for the first time the problem of undesirable outputs production taking an intersectoral perspective without losing the microeconomic dimension. Thanks to the European Pollution Release and Transfer Register data collection is guaranteed in an homogeneous way from each industrial site, characterised by industrial capacity and emission levels over specific thresholds. Environmental and economical efficiency are then both estimated using balance sheet data as proxies of input usage and good output production, while two indexes of environmental impact represents emission levels. An opportunity cost of environmental protection is derived at firm level, computing the potential turnover loss due to environmental protection. The main findings are in line with previous literature: considering bad outputs changes significantly the best practice frontiers and reduce mean observed inefficiency. The adoption of the so called Best Available Technique promote a good starting level of environmental protection as the high average level of efficiency shows. All the results obtained by solving linear problems, are analysed in a structured second stage phase, using one of the most modern econometric technique for robust statistical inference. Individual characteristics of each firms are included as control variables in order to test some hypothesis in a more precise way and this approach is relatively new to the case of DDF. Statistically different levels of eco-efficiency among industries emerge both under weak and free disposability of bad outputs, but the evidence is less strong for estimated regulatory costs. Some technological differences, strongly related to each particular production process, emerge, as partially expected, both in term of performances and potential good lost due to environmental protection. About this latter variable, empirical evidence regarding firms' size and performances is more clear: large firms are more able to face complex environmental rule and their technology allow to better exploit scale economies, also when emissions are considered. Of course results should be interpreted and extended with care, especially in the second stage phase, but some interesting policy implication could be derived. The introduction of new environmental principle or standard and the obligation to adopt more cleaner technique could have some positive effect on green efficiency which can or cannot be evaluated in term of their costs. However also if this aspect is disregarded, new complex rule has a stronger effect on small industrial sites, imposing additional costs and bureaucracy. The reaction of SMEs is probably a contraction of production capacity, consequentially of turnover, to exit from registers and from their regime of emission control. The common idea that environmental protection is more pervasive for big industrial sites because SMEs are more flexible is then partially reversed. This is one of the open issues needing further investigation and is particularly interesting in countries such Italy where the presence of small firms is important. Moreover obtained results suggest that one possible way to reduce the impact of environmental rule is to sustain firms capitalisation. Equity remuneration could be partially scarified in the name of long term strategy aimed at enhancing green performances able to guarantee an higher sustainability for the future. Such considerations are obviously less easily accepted by an external subject, that is more interested, by its nature, in short term capital refunding. These friction of objective could create additional costs in under-capitalised firms by imposing pollution abatement solution with short time horizon, rather than more complete re-thinking of business strategies able to create environmental sustainable opportunities in the long term.

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Chapter 3

External funding, efficiency and productivity growth in public research: the case of the Italian National Research Council

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Abstract

This paper presents an application of the Directional Output Distance Function (DODF) model to measure the internal performances of the Italian National Research Council (CNR). Research institutes are seen as Decision Making Units (DMUs) which produce two different kinds of scientific outputs using inputs. We consider some outputs more important from a scientific point of view than others, which we refer to as bad. Financial constraints, recently imposed by the government, do not allow the institutes to freely dispose of their output portfolio and bad outputs have to be produced in order to obtain external funds. Using the DODF framework it is possible to estimate the effect of fund cuts in terms of potential scientific products lost. By applying the Malmquist-Luenberger indexes we produce evidence on the trend of Total Factor Productivity (TFP) after the 2003 internal restructuring process. A comparison of results within the standard efficiency framework is provided and the big differences that emerge allow us to draw alternative conclusions on the recent evidence.

JEL classification: D24, I20, I23, I28
Keywords: Public research, Directional Distance Function, Malmquist-Luenberger productivity indexes

3.1 Introduction

Since the first restructuring of the CNR in 1999, one of the main goals of all interventions has been to recover efficiency and reduce costs. Indeed, Cesaroni and Piccaluga (2002) underline that, since the 1980s, as a consequence of financial crises the Governments have progressively reduced research funds inducing research institutes and universities to adopt a managerial vision (Etzkowitz *et al.*, 2000). Considering this, the last 2003 restructuring was focused on increasing the institute's collaboration with the industry, the local institutions (Coccia and Rolfo, 2008) and firms (Tuzi, 2005).

The first aim of increasing knowledge and innovation through technological spillovers is at least as strong as the need to cut costs. Researchers have to partially rethink their position in order to be able to attract funds on the market by offering their skills to external institutions. This process is common to all industrialised countries, even though to different extents (Geuna and Nesta, 2006), but it is particularly important in some scientific fields where fund cuts create strong financial problems. Geuna (2001) shows that universities have gradually been obliged to diversify research funding because government structural funds have substantially declined and research institutes have searched for alternative funds. It should be noticed that external funding is often also related to patenting activity. Nevertheless, it is clear that patenting is an extremely difficult and rare event because it requires an expensive process and not all innovations generate sufficiently profitable revenues. Moreover, not all research fields give results suitable for patenting, i.e. it is rather difficult to think of patenting in the history field. Geuna and Nesta (2006) propose a descriptive table on patents obtained from different countries. Considering an example from Italy, the three technology/science areas which have more patents are: Biotechnology, Drugs and Organic Chemistry. Almost the same areas are cited for the other countries analysed in their work.

Another point to investigate concerns the CNR's reform, which is not strictly coherent. Indeed, although the aims have changed, the evaluation criteria have not been updated and researchers' careers are still evaluated on the basis of their scientific production, interpreted in terms of ISI or refereed papers or books or patents[1]. From this point of view the situation is slightly different in other EU countries, e.g. in France, where researchers are incentivised on the basis of the relationships they establish within research activities

[1]This link $http : //www.urp.cnr.it/copertine/formazione/$ $form_{c}oncorsi/concorsi2009/364-88art15.pdf$ shows a CNR competition notice for the career progress of researchers with details on evaluation criteria.

and technology transfer[2] (Llerena *et al.*, 2003).
Considering previous remarks, researchers have started ever more frequently to look for external projects to fund the activities of their research institute, paying more attention to report writing. Indeed, the reporting activity represents the desired output for the external client but not for the researcher, because it does not contribute to career progress. In particular, what seems to emerge from internal careers and fund distribution is that institutes which are better at publishing scientific papers are the most appreciated.
In this regard, the situation of research entities is worsened by the uncertainty around performance measures in the scientific production field. How to evaluate the efficiency of researchers and research institutions remains an open question.
Of course, a principal-agent problem arises with strong consequences on funding schemes: the government gives money but it is unable to truly control who is producing something useful. Nevertheless, the concept of useful in the field of science is something that remains an open issue on which the literature is still discussing. Pavitt (1998) clearly says that *the main goal of scientific research is to produce codified theory and models that explain and predict natural reality*, but at the same time he defines the output of business and applied research as useful artefacts. He also shows how basic research and technological development differ in terms of actors, purposes, skills and outputs. That taxonomy clearly shows the hybrid condition of the Italian National Research Council, devoted in part to pure theoretical activities following its historical vocation, but also to more applied research in order to establish closer linkages with firms.
Given the complexity of the topic, our goal is not to contribute to a complete definition of research objectives. We start from the idea that a portfolio of scientific products has to be produced by each institutes in order to meet multiple objectives. Researchers focus their attention on subsets of outputs which are able to boost their career, but they must also find external funds and compile marketable scientific products. The aim of this work is to build a model of performance evaluation based on the idea that different kinds of outputs are jointly produced in a public research body. Some outputs are scientific products, characterised by international relevance and novelty, but another group of outputs is less likely to stand out because more applied and focused on local problems: they are "grey literature"[3].

[2]Technology transfer is the diffusion of the complex bundle of knowledge which surrounds a level and type of technology. For a thorough explanation of this concept, see Charles and Howells (1996).

[3]A close examination and definition of "grey literature"has been provided at the $12^t h$ International Conference on Grey Literature held in Prague in December 2010. Considering the Prague Definition " *Grey*

3.2 Literature review

Reducing costs and improving productivity are the goals of the last reform but how can the efficiency and the productivity of universities and research institutes be measured? In particular, the question does not concern the methodological approach but the exploration of determinant variables of efficiency and productivity. This topic has been studied for a long time and in Italy it is more and more relevant because it is connected with the problem of researcher evaluation. Indeed, if the vision of research institutes must be market-oriented also the production of researchers has changed, even though their evaluation criteria are always the same. Sure enough the new external commitments finance applied researches to generate reports or, in certain fields, patents but not often scientific publications. Considering this point, there is a certain correlation between the origin of funding and the kind of research production. Groot and García-Valderrama (2006) analyse results from 169 Dutch research groups considering the origin of their funds. The authors find that the amount of national funding is positively related to academic quality, whereas the gains from external research commitments are negatively related to academic quality. This finding seems to suggest that the increasing weight of committed research, necessary after the financial crisis, shifts the focus of researchers more and more towards applied studies. Nevertheless, if this change is required by macroeconomic evidence, it becomes necessary to reconsider the concept of *quality* in research activity and the evaluation of research and researchers.

In literature many studies have considered the problem of allocation of funds in research activities (e.g.: Davidson, 1957; Lyall, 1978, Cohn *et al.*, 1989; Madden *et al.*, 1997) but it is very difficult to evaluate performances of research centres on the basis of profits or losses, in an economic sense. Indeed, public sector organisations and universities usually present different outputs as results of their activity, such as publications in scientific reviews or patents or research grants and so on. Each output has a different quality evaluation and perception, hence to assess the performances of these centres it is necessary to use a methodology that considers technical outputs as real evidence of good or poor performance.

To achieve this goal authors usually estimate cost functions with a focus on economies of

literature stands for manifold document types produced on all levels of government, academics, business and industry in print and electronic formats that are protected by intellectual property rights, of sufficient quality to be collected and preserved by library holdings or institutional repositories, but not controlled by commercial publishers i.e., where publishing is not the primary activity of the producing body"(Schöpfel and Farace, 2010).

size and scope (Throsby, 1986; De Groot *et al.*, 1991; Lloyd, 1994; Dunbar and Lewis, 1995; Hashimoto and Cohn, 1997) or through the Data Envelopment Analysis (*DEA*) that has been selected by several researchers as a suitable tool (Athanassopoulos and Shale, 1997; McMillan and Debasish, 1997). Tomkins and Green (1988) underline that the only way to build an overall efficiency index is by using a weighted sum of outputs; the problem is how to assign these weight. In their work Johnes and Johnes (1995) state that the *DEA* methodology allows assigning efficiency scores without needing to make arbitrary assumptions about the weighting scheme to be attached to various types of output. Kao and Hung (2008) study the efficiency of different departments of the National Cheng Kung University in Taiwan (*NCKU*) using the Data Envelopment Analysis approach and cluster analysis technique. In this study, the authors analyse inputs to insert into the model on the basis of several considerations on the Taiwanese university system. They select personnel, expenses, and floor space. Inserted outputs are teaching load, publications, and external grants. After the efficiency analysis, the paper shows via cluster methodology the aggregation of departments in four clusters on the basis of best efficiency. This is a very interesting procedure to highlight the area in which departments need more care and/or more financial resources.

Concerning to Italy situation interesting is the study depicted by Abramo *et al.* (2011) in which efficiency scores of Italian research institutes have been evaluated through DEA approach.

An alternative methodology to *DEA* is the use of stochastic production or stochastic cost frontiers (Coelli *et al.*, 1989) but this technique has the disadvantage of needing assumptions regarding the functional form of the best practice frontier. Therefore, this approach has not been widely used in the literature (Johnes and Johnes, 1995).

Once it has been established that the *DEA* methodology is a good tool for assessing technical efficiency, another question is about the selection of variables to introduce into the model because depending on inputs and outputs the meaning of the efficiency score can change. Sarrico *et al.* (2009) use a linear mixed-effect model methodology allowing for random effects at university level to measure the productivity of Portuguese public universities, taking into account their subject composition. Indeed, correlation among observations from the same university arises from sharing unobserved variables. Tuzi (2005) underlines that good quality scientific production and technology are linked assuming the number of patents as a proxy of technological production. In this field, the contribution by Calderini *et al.* (2007) is also important because it shows a mutual positive correlation between patenting and top journal articles. In this sense, also Abramo and Lucantoni (2003) already highlighted that the CNR should capitalise on its patenting efforts by turning them into scientific publications with the aim of diffusing knowledge and increasing research quality.

Following previous literature, in this study a DEA frontier has been built, but drawing the concept of Directional Distance Function (DDF) from the pollution field. This concept allows introducing qualitatively different outputs. This new idea of flexible distance was proposed by Chambers *et al.* (1996) and it encompasses input and output distance function maintaining additive features. The theoretical properties of DDF are analysed in Chambers *et al.* (1998) and Färe *et al.* (2000). The strong point of DDF is the possibility of modifying the direction in which to search for the efficient counterpart of each firm. This allows changing the concept of productivity without modifying technology representation via data transformation. The applications are numerous especially in environmental fields; for example, Boyd *et al.* (2002) analyse US glass manufacturers, Picazo-Tadeo *et al.* (2005) and Picazo-Tadeo and Prior (2009) Spanish ceramic industries, McMullen and Noh (2007) public transport, and Kumar and Managi (2010) power generating firms. The only empirical study where the DDF approach is explicitly used to build scientific production technology has been carried out by Glass *et al.* (2006), but the DDF is applied by exploring profit function features rather than pure scientific efficiency.

3.3 Modelling scientific efficiency with necessary but undesirable outputs

To model the scientific production function of CNR institutes, three types of variables are defined: inputs, *good* outputs and *bad* outputs. This last category is the key point in our approach because it represents research outputs which are particularly linked to external funds. Reports and other unspecific publications are examples of this concept: each researcher has to guarantee the production of "*bad*"outputs in order to show committed research activity. Institutes cannot reduce these works without fund cuts that would imply a reduction in desirable or *good* outputs. Indeed, CNR funds are not sufficient to cover ordinary costs such as computer maintenance, telephone, electricity, journal subscriptions or data access and so on. Hence, to produce desirable outputs from a scientific point of view, the *bad* production becomes necessary.

This idea of introducing *bad* outputs in the scientific production function is translated into two axioms which are added to the classical production technology framework. Let $x = (x_1, ..., x_N) \in R_+^N$ be a vector of inputs, $y = (y_1, ..., y_M) \in R_+^M$ a vector of scientifically desirable outputs *good* and $b = (b_1, ..., b_J) \in R_+^J$ a vector of undesirable but necessary outputs *bad*, the output set could be written as:

$$P(x) = \{(y, b) : x \quad \text{can produce}(y, b)\}, x \in R_+^N \tag{3.1}$$

The output set $P(x)$ consists of *good* and *bad* output combinations that could be produced using an input vector x. Following Färe et al. (2007), some standard axioms are satisfied by scientific technology with bad outputs:

1. *Inactivity*. Each institute might choose to remain inactive in its scientific production $0 \in P(x), \forall x \in R_+^N$;

2. *Compactness*. $P(x)$ is compact (finite x gives finite (y, b));

3. *Free disposability of inputs*. Inputs are freely disposable $P(x) \subseteq P(x')$ if $x' \geq x$, then each institute might always obtain the same amount of outputs if input quantities increase;

4. *Null jointness*. If the amount of bad outputs, strongly linked to external funds, is equal to zero it is not possible to produce good outputs because ordinary costs cannot be covered. In notation:

$$\forall y \in Y, \forall b \in B, b = 0 \Longrightarrow y = 0$$

5. *Weak disposability of outputs*. Weak disposability is a concept created in the environmental field: if there are some outputs which are undesirable it is reasonable to assume that bad outputs might not be reduced without also reducing good outputs. In our model of scientific production the effect is indirect and influenced by the moderated effect of the inputs reduction: if bad outputs are reduced, external funds decrease and ordinary costs cannot be covered. This implies a subsequent drop in scientific output, which might go as far as the extreme case of absence of external funding causing zero *good* output production. Of course a research centre might decide to reduce *bad* outputs, but only a proportional reduction of both *good* and

bad outputs is feasible. In notation, let $P(X)$ be the production possibility set and $0 \leq \alpha \leq 1$:

$$(x, y, b) \in P(x) \Longrightarrow (x, \alpha y, \alpha b) \in P(x)$$

6. *Free disposability*. The standard hypothesis continues to hold for desirable outputs only, then a reduction of *good* outputs maintaining inputs and *bad* outputs fixed is always possible.

$$\begin{aligned}(x, y, b) \in P(x) &\Longrightarrow (x, \alpha y, b) \in P(x) \\ &\Longrightarrow (x, y, \alpha b) \notin P(x)\end{aligned}$$

The Directional Output Distance Function (DODF) gives the maximum feasible proportional contraction in *bad* outputs and expansion in *good* outputs (Chambers *et al.*, 1996). DODF is defined on $P(X)$ and takes a value equal to 0 for efficient DMU which contributes to the frontier identification and increases with inefficiency, formally:

$$\begin{aligned}\overrightarrow{D}_0^W(x, y, b; g_y, g_b) &= \\ \max\{\beta &: (y, b) + (\beta g_y, \beta g_b) \in P(x)\}\end{aligned} \tag{3.2}$$

where $g = (g_y, g_b)$ is the directional vector and $P(x)$ is the production possibility set estimated via DEA by solving, after fixing a particular directional vector and for each institute, the linear problem that identifies the best practice frontier. Assuming that institutes are not worried about reducing necessary outputs, then we assume a directional vector $g = (y, 0)$.

Following the previous assumption on the output set, the value of directional distance might be estimated using linear programming:

$$\begin{aligned}\overrightarrow{D}_0^W(x^k, y^k, b^k; y^k) &= \max \beta \\ \text{s. t.} \quad x^k &\geq Xz \\ (y^k + \beta y^k) &\leq Yz \\ b^k &= Bz \\ z &\in R_+^k\end{aligned} \tag{3.3}$$

The directional output distance function re-scales the observed output vector (y,b) on the

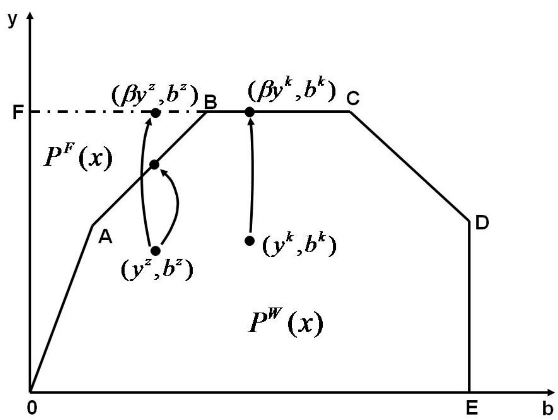

Figure 3.1: Production sets, efficient projections and directional vector

frontier following the g direction, that is $(y, 0)$ in our case. Keeping in mind our g, when $\overrightarrow{D}_0^W(x^k, y^k, b^k; y^k) = 0$ institute k is on the frontier or, in other words, there does not exist another institute - or a linear combination of efficient firms - able to produce a larger amount of good outputs without using more inputs or *bad* outputs. A value of $\overrightarrow{D}_0^W(x^k, y^k, b^k; y^k)$ greater than zero gives the level of inefficiency and in particular the technically feasible expansion of good outputs.

Using the DODF framework the production technology is represented in a way immediately derived from reality, without transformations, and every constraint in the estimation of $P(X)$ can be formulated in linear form and thanks to the additive nature of DODF the DEA framework is immediately applicable.

3.3.1 The regulatory impact indicator

Taking advantage of results found by Färe *et al.* (1989) in the environmental field, some studies try to estimate the total burden due to weak disposability on outputs. The underlying idea is that the regulations reduce output combinations by introducing costs on bad outputs. In the research context, the funding scarcity prevents the free distribution of efforts in the scientific production and *bad* outputs have to be produced. This constraint modifies the shape of the best practice frontier through weak disposability. Imagining to decrease weak disposability from our 6 axioms, the output set and our piece-wise linear frontier can be estimated as if fund cutting disappeared. Of course, some limitations arise: it is only possible to detect departure from the actual estimated weak disposable frontier to a free disposable one. Linear problems remain the same, but the last equality is replaced by an inequality with an unchanged directional vector:

$$\begin{aligned}
\overrightarrow{D}_0^F(x^k, y^k, b^k; y^k) &= \max \beta \\
\text{s. t.} \qquad x^k &\geq Xz \\
(y^k + \beta y^k) &\leq Yz \\
b^k &\leq Bz \\
z &\in R_+^k
\end{aligned} \tag{3.4}$$

This means that it is possible to decrease bad outputs without costs, i.e. without reducing financial resources in the CNR case. In other words, this is equivalent to assuming that self-financing constraints do not exist anymore, and by comparing this two sets of results it is possible to create a proxy of scientific output loss due to the regulations. Figure 3.1 provides a graphical representation of what explained before: the directional vector $g = (y, 0)$ assumes a vertical shape because the horizontal axis represents *bad* outputs. Weak disposability modifies $P(X)$ only in the first part of the frontier, while in the remaining cases the estimation of the free disposable output set coincides with its weak disposable counterpart. Following Picazo-Tadeo and Prior (2009) with the chosen directional vector the indicator of potential output lost takes the form:

$$RI = \overrightarrow{D}_0^F(x^k, y^k, b^k; y^k) - \overrightarrow{D}_0^W(x^k, y^k, b^k; y^k) \tag{3.5}$$

This index can only give a partial proxy of the cost imposed on the institutes, which have to rethink their role. As Zofio and Prieto (2001) underline, this methodology measures the regulatory impact and the fund cutting in the CNR case if and only if no intervention existed before. If the institutes are somehow forced to search for external financial resources, it will not be possible to identify the real free disposable frontier. All invisible costs borne through the years to become externally attractive could not be measured and also the potential scientific output loss could not be exactly derived. The only effect that can be measured in case of weak disposability is the visible departure from the actual best practice frontier to an hypothetical free disposable one, which derives from all previous choices taken under financial constraints. Keeping this limitation in mind and using a sort of simulated reality, by combining results from both sets of linear problems, it is possible to create a proxy of the impact of fund cutting in terms of potential output loss.

3.3.2 Productivity growth indexes

The new definition of distance based on directional vectors allows re-defining the classic Malmquist indexes, as Chung *et al.* (1997) demonstrated. By comparing mixed technology between time t and $t+1$, the so called Malmquist-Luneberger indexes (ML) can be derived, assuming the DODF rather than the standard radial distance. Weber and Domazlicky (2001) suggest:

$$ML_t^{t+1} = \Big[\frac{(1+\overrightarrow{D}_0^t(x^t, y^t, b^t; g^t))}{(1+\overrightarrow{D}_0^t(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1}))} \cdot \frac{(1+\overrightarrow{D}_0^{t+1}(x^t, y^t, b^t; g^t))}{(1+\overrightarrow{D}_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1}))}\Big]^{\frac{1}{2}} \tag{3.6}$$

where the output directional vectors g^t and g^{t+1} are assumed respectively $g^t = (y^t, 0)$ and $g^{t+1} = (y^{t+1}, 0)$. These indexes maintain all the peculiar features of the classic Malmquist growth indicators, but in addition they are able to combine all the previous considerations on output set and asymmetric treatment of output categories (Kumar, 2006). The ML indexes are particularly useful in measuring scientific performance where output prices cannot be derived[4]. The ML index, called Total Factor Productivity (TFP), is built as the geometrical mean of two components - one based on technology at time *t* and one based on technology at time *t+1* - which represent the ratio of the DODFs calculated on quantities at time *t* and *t+1*. The TFP might be divided in two parts: the former representing the efficiency gain over the time period (*EFF*), the latter accounting for technical progress in the scientific production function (*TECH*):

$$EFF_t^{t+1} = \frac{1+\overrightarrow{D}_0^t(x^t, y^t, b^t; g^t)}{1+\overrightarrow{D}_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1})}$$

[4]This is a big problem when using the Fischer or Törnqvist indexes, which on the contrary require also information on market prices.

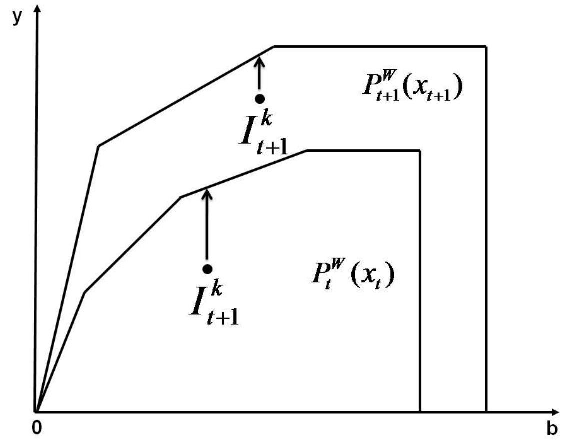

Figure 3.2: Frontiers over time period and TFP growth assuming $g = (y, 0)$

The EFF component represents the catch-up effect of inefficient institutes with respect to the new *t+1* frontier.

$$TECH_t^{t+1} = \Big[\frac{(1+\overrightarrow{D}_0^{t+1}(x^t, y^t, b^t; g^t))}{(1+\overrightarrow{D}_0^{t}(x^t, y^t, b^t; g^t))} \cdot \frac{(1+\overrightarrow{D}_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1}))}{(1+\overrightarrow{D}_0^{t}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1}))}\Big]^{\frac{1}{2}} \tag{3.7}$$

The TECH component describes the frontier shift occurred from *t* to *t+1* and it represents a proxy of technological change between the two time periods. This component can be 0 if the analysed subject is efficient in both periods; negative values are allowed but they are difficult to interpret. They are normally attributed to the estimation method, unable to distinguish between EFF and TECH in case of fully efficient subjects. Following Oh and Helmati (2010), figure 3.2 represents the case of our specific directional vector and suitably describes the position of the CNR, where *bad* output production is increasing over time. To simplify matters, $x_t = x_{t+1}$ is assumed in order to depict both weak disposable frontiers in a single graph. TFP is increasing between *t* and *t+1*, the same holds true for efficiency and technological progress.

3.4 Data

We use only public data for the 2004-2007 period, available online from the institutional CNR website. Data coverage is around 90% of the entire population. There are 110 CNR institutes (from the CNR website) divided into 11 departments on the basis of their scientific fields. Data from 12 institutes are missing[5]. The database is a balanced panel of 98 subjects observed in 2004, 2005 and 2007. The CNR institutes are centres that, from the input disposability point of view, produce different kinds of research outputs (*good* and *bad*). Which the outputs of the research activity are - and how to evaluate their quality - still remains an open issue, as underlined in the introduction[6] .

The empirical literature on scientific production is very broad and many approaches are followed ensuing from a wide range of views on science, in the wake of Pavitt. In some works the output is represented only by high-quality scientific production; for instance, in Saricco (2009) scientific productivity is measured in terms of ISI articles[7]. Cherchye and Abeele (2005) adopt an intermediate view: they consider doctoral dissertations, refereed articles in international journals and books and they exclude non-refereed article and reports. Glass *et al.* (2006) create an indicator of research outputs based on both quantity and quality of written articles. Johnes and Johnes (1995) identify many scientific outputs like papers in academic journals, letters in academic journals, articles in professional journals, articles in popular journals, authored books, edited books, published official reports and contributions to edited works. Abbott and Doucouliagos (2003) analyse the productivity of Australian universities distinguishing between teaching and research activity, but the problem is always the same: agreeing on how to evaluate the research output.

Based on previous considerations, in this study all kinds of outputs are considered, but the DDF methodology allows categorising them in two classes: *bad* and *good*, i.e. the "desirable"publications - or patents - and the "necessary"ones. Hence, inputs and outputs introduced in the model are 4 desirable (*good*) outputs, on which researchers concentrate their efforts in order to increase internal and external reputation (ISI articles, refereed

[5]These institutes are going through a restructuring phase and data on research outputs or financial resources are not available.

[6]See Franceschet and Costantini (2011) for a thorough analysis on the necessity of a rating system for the evaluation of scientific research outputs.

[7]The Institute for Scientific Information (ISI) was founded by Eugene Garfield in 1960 but now it is a part of the Thomson Reuters Corporation. ISI offered bibliographic database services. Its specialty: citation indexing and analysis, a field pioneered by Garfield. It maintains citation databases covering thousands of academic journals, including a continuation of its longtime print-based indexing service, the Science Citation Index (SCI), as well as the Social Sciences Citation Index (SSCI), and the Arts and Humanities Citation Index (AHCI). All of these are available via ISI's Web of Knowledge database service. This database allows a researcher to identify which articles have been cited most frequently, and who has cited them. The ISI also publishes the annual Journal Citation Reports which list an impact factor for each of the journals that it tracks. Within the scientific community, journal impact factors play a large but controversial role in determining the kudos attached to a scientist's published research record.

non ISI articles, books and patents), 2 necessary (*bad*) outputs linked to external projects (reports and other editorial activities), and 6 inputs involved in the scientific production process and representing human and financial resources. Inputs and outputs have been chosen on the basis of previous Italian researches (Coccia, 2008), making some adjustments thanks to the flexibility of the DDF methodology and the possibility of introducing *bad* outputs and more detailed inputs. Data on employees and financial data have been extracted from the CNR's balance sheets in which data are aggregated by institutes. Human resources are divided in three different categories, each characterised by a different contribution to scientific activity: researchers, technicians and administrative staff. Funds are classified according to their origin with the following idea:

- *Funds from the CNR*: the CNR's financial administration covers all costs for payroll employees. This quantity allows controlling for employee recruitment (e.g.: researcher or senior researcher);

- *Ordinary funds*: these are directly managed by each institute. We suppose that they represent a proxy of capital stock[8];

- *External funds*: these are resources coming from external subjects for specific and committed researches.

Data on outputs are obtained by merging research production data available on the web page of each institute. These data are updated thanks to a collection mechanism based on self-declaration by each researcher at the time of publishing.
Table 3.1 shows summary statistics for the inputs and outputs used in the analysis. The values refer to 2007, while data on 2004 are not reported.

A high degree of heterogeneity in the institutes' dimension, considering both human resources and financial budgets, emerges from the table. Taking outputs into consideration, differences increase because institutes have very different research fields, so an institute is more likely to patent rather than to publish books.

[8]These funds are distributed on the basis of past allocation, but they are higher in case of a big laboratory or complex machinery.

Table 3.1: Summary statistics of inputs and outputs observed in 2007, by institute

	mean	sd	min	max
Inputs				
Researchers	36.8	23.2	6.0	158.0
Technicians	17.0	15.7	2.0	128.0
Administrative staff	5.8	5.8	0.0	46.0
Funds from CNR 000	7,164	8,857	353	81,486
Ordinary Funds 000	715	576	54	3,158
External Funds 000	2,132	5,283	7	50,828
Good Outputs				
Patents	1.1	2.1	0.0	10.0
ISI articles	54.0	46.4	0.0	208.0
Non ISI articles	15.0	17.3	0.0	111.0
Books	14.3	17.2	0.0	85.0
Bad Outputs				
Reports	15.9	23.7	0.0	146.0
Other publications	3.1	7.0	0.0	54.0

3.5 Results

3.5.1 The efficiency path

In this section efficiency results for four different frameworks of directional distance function are shown. In table 3.2[9] the first column represents the inefficiency value of each department assuming weak disposability on *bad* outputs and constant return to scale. From this analysis Cultural Identity and Cultural Heritage are the most efficient departments, whereas Energy & Transportation and Advanced Manufacturing Systems are the most inefficient departments.

Removing the hypothesis of weak disposability we allow for a costless reduction in bad outputs, as the ordinary funding might be able to cover costs of inputs. Within this paradigm, the Cultural Identity department shows the best performance, whereas Medicine has the worst.

The last two columns have been introduced to compare results with standard DEA technique. In the last column all outputs are considered good and then they are all maximised in the optimisation program, whereas the third column considers only articles, books and patents as results of the scientific production.

[9]Institutes were grouped in 11 departments after the 2003 restructuring of CNR. These groups were created on the basis of the specific mission of the institutes.

All these results show that the Cultural Identity department is the most efficient in doing scientific research. Our findings seem to confirm the absence of a crowding-out effect (Coccia and Rolfo, 2008) in social sciences due to external funding. This is due to the greater need for financial resources that characterises the hard sciences. Big laboratories and costly equipment force institutes to devote more time to external research and this implies higher inefficiencies.

Table 3.2: Efficiency results by departments

Departments	D(0,y) CRS weak	D(0,y) CRS free	No bad outputs	All good outputs
Agriculture & Food	0.349	1.003	1.195	0.865
Energy & Transport	0.791	1.079	1.263	0.818
ICT	0.147	0.377	0.709	0.313
Cultural Identity	0.017	0.082	0.360	0.002
Materials & Devices	0.254	0.437	0.568	0.413
Medicine	0.268	1.222	1.332	0.815
Cultural Heritage	0	0.679	0.946	0.283
Molecular Design	0.123	0.331	0.404	0.283
Life Sciences	0.148	0.944	0.971	0.913
Advanced Manuf. Sys.	0.544	0.801	1.427	0.479
Earth & Environment	0.341	0.635	1.120	0.382
Total sample	0.241	0.625	0.860	0.454

Source: our elaboration on public data

As expected, in table 3.2 inefficiency is always increasing from left to right, with the exception of the last column where a different approach is adopted and all the outputs produced are considered good. Focusing on first three columns, the estimated inefficiency increases with the stringency of evaluation criteria adopted by the central CNR office or by external entities. From weak to free disposability on bad outputs the individual average inefficiency rises from 0.24 to 0.62, assuming the same distance vector. If bad outputs are not considered, in the most *strictly scientific* view, inefficiency grows to 0.86. Therefore, as done in several previous articles in the field of scientific production technology, ignoring bad outputs in the efficiency evaluation leads to major underestimation of average productivity. This bias could be partially corrected if a mixed approach was adopted and all the outputs produced were considered good. In this case, shown in the fourth column in table 3.2, inefficiency is almost halved, decreasing to 0.45. However, in this way we are assuming that reports and all other publications are also main objectives of researchers in order to increase their status, but this is not currently the case in CNR.

3.5.2 The Fund rationing and the potential output lost

By comparing efficiency results under weak and free disposability it is possible to obtain a proxy of *fund rationing* effect on potential good output. We run the analysis not only for 2007 but also for the starting observation year, i.e. 2004. Results reported in table 3.3 show that the burden imposed on CNR research units is increasing over time and the effect of fund rationing is higher and higher in terms of potential good outputs lost. The initial value of 13% is increasing by 42% to over 19% at a medium annual rate of 12.5%. The situation is heterogeneous and big differences arise at department level: Agriculture & Food, Cultural Heritage, Energy & Transportation and Advanced Manufacturing Systems seem to greatly suffer from the impossibility of freely disposing of outputs. This does not mean that these departments are the most inefficient, but that their efficient counterpart should change more under free disposability of bad output. The zero impact of fund rationing on the Cultural Identity department must be considered only as a spurious result due to the full efficiency of the department in relation to the deterministic frontier.

Table 3.3: Fund cutting impact in 2004 and 2007

Departments	2007 Fund cutting indicator	2004 Fund cutting indicator
Agriculture & Food	0.399	0.145
Energy & Transport	0.296	0.130
ICT	0.213	0.200
Cultural Identity	0	0.010
Materials & Devices	0.174	0.081
Medicine	0.196	0.314
Cultural Heritage	0.310	0.332
Molecular Design	0.164	0.053
Life Science	0.153	0.233
Advanced Manuf. Sys.	0.229	0.123
Earth & Environment	0.281	0.099
Total Sample	0.194	0.136

Arithmetic mean of individual values, 3 outliers excluded

In order to better understand the real fund cutting effect, for each observed portfolio of scientific products the equivalent in physical quantity of the output indicator has been calculated. This procedure leads to a total output loss able to account for differences in the institutes' aptitude to scientific production.

Results in table 3.4 show the strength of our approach: more than 800 ISI papers are missing due to fund constraints imposed on the CNR and also for the other categories of outputs the evidence is impressive. If an individual perspective is adopted, each institute could be able on average to produce 10 between ISI and non ISI articles, 2 books and $\frac{1}{10}$ of a patent. The largest production might be achieved by Energy & Transportation, Materials & Devices, Medicine and Earth & Environment, considering only ISI; Molecular Design, Medicine, Life Science and ICT if a purely technological perspective is preferred.

Table 3.4: Potential good outputs lost in 2007

Departments	ISI articles	Non ISI articles	Books	Patents
Agriculture & Food	10.7	4.1	4.2	0
Energy & Transport	14.0	0.4	0.9	0.06
ICT	8.8	1.98	1.3	0.15
Cultural Identity	0	0.003	0.01	0
Materials & Devices	11.0	1.1	0.8	0.05
Medicine	11.7	2.4	2.0	0.19
Cultural Heritage	2.0	5.1	7.3	0
Molecular Design	11.4	1.3	0.5	0.23
Life Science	9.4	0.4	0.08	0.15
Advanced Manuf. Sys.	6.1	1.4	1.38	0.07
Earth & Environment	11.6	4.3	4.3	0.01
Total sample	8.8	1.9	1.8	0.09
Cumulative loss	849	186	174	8.7

Arithmetic mean of individual values, 3 outliers excluded

3.5.3 The TFP growth in the 2004-2007 period

Thanks to the approach outlined in the theoretical section, a comparison between productivity performance in 2004 and 2007 has been made, assuming both the with and the without bad output hypothesis.

In table 3.5 we report the Malmquist-Luenberger indexes calculated assuming two bad outputs and four good outputs and the results suggest a mean productivity growth of around 11% during the three years. The departments where the productivity grows the most are Cultural Heritage, Advanced Manufacturing Systems and ICT; whereas Agriculture & Food grow slowly and Molecular Design does not grow in terms of productivity. This methodology allows us to separate the effect on the productivity of changes in the frontier due to technical progress and efficiency recovery. In our case efficiency recovery (table 3.5, third column) is positive[10] for all departments, except Molecular Design and Materials & Devices. These negative values reflect an inwards shift of the frontier, a process that is hardly plausible. A possible interpretation, as Domalizlicky and Weber (2004) suggest, is that we only observe an estimation of the best practice frontier, whereas the true technology remains unobserved. Considering the CNR institutes on the estimated piece-wise linear frontier, the model is not able to split the productivity growth into technical change and efficiency gain. The DDF formulation describes this shift as a negative technical change, but it is probably due to an efficiency reduction in comparison to the real and unobserved technology frontier. When bad outputs are considered and they are not maximised by institutes, the productivity growth is determined by both efficiency gains and technical progress with the same magnitude effect. The Cultural Identity department displays one of the lowest growths, but its components are fully efficient and hence they contribute to driving the estimated frontier: the efficiency gains are limited to good performances in terms of growth. With the aim of better understanding the previous results,

Table 3.5: Malmquist-Luenberger results with both good and bad outputs

Departments	ML	TECH	EFF
Agriculture & Food	1.016	0.969	1.048
Energy & Transport	1.132	1.110	1.020
ICT	1.165	1.119	1.041
Cultural Identity	1.045	1.022	1.022
Materials & Devices	1.048	1.063	0.985
Medicine	1.130	1.074	1.053
Cultural Heritage	1.370	0.875	1.567
Molecular Design	0.977	1.037	0.943
Life Science	1.122	1.124	0.999
Advanced Manuf. Sys.	1.340	1.135	1.180
Earth & Environment	1.157	1.115	1.038
Total sample	1.108	1.059	1.046

Geometric mean of individual scores, 3 outliers excluded

the Malmquist indexes are calculated considering all outputs as good. Table 3.6 shows our findings. What immediately emerges is that the standard Malmquist indexes present a

[10]Values smaller than 1.

higher growth in productivity - 20% more compared to Malmquist-Luenberger - and this is in contrast with Chung *et al.* (1997) and Weber and Domazlicky (2001). The previous literature underlines how both-sign biases are consistent with the model when bad outputs are missing. However, previous empirical findings often reveal a negative bias on the estimated TFP growth if bad outputs are ignored. In our analysis the same emerges too, but results collected in table 3.6 show Malmquist indexes for the case in which bad outputs are considered good. From this point of view, it is difficult to compare our findings to other contributions. Table 3.6 displays negative mean efficiency gains, with a consequent deterioration of the distance in relation to the frontier from 2004 to 2007, which is inconsistent with our previous results under the Malmquist-Luenberger approach.
Ignoring bad outputs therefore has a double effect. First of all, a different productivity dynamic arises; in particular, the difference between the 2 approaches is around 20% and this evidence remains statistically significant after both parametric and non parametric tests. Secondly, the breakdown of the TFP growth is impressively different under the two approaches: if all outputs are considered good, only the technical change component seems to drive the productivity growth. The conclusions in this case are radically different: the CNR restructuring does not have a positive effect on efficiency recovery in research institutes.

Table 3.6: Standard Malmquist results assuming all outputs as good

Departments	ML	TECH	EFF
Agriculture & Food	1.141	1.212	0.941
Energy & Transport	1.291	1.112	1.162
ICT	1.196	1.174	1.019
Cultural Identity	1.163	1.148	1.013
Materials & Devices	1.044	1.106	0.944
Medicine	1.267	1.173	1.080
Cultural Heritage	1.182	1.259	0.939
Molecular Designs	1.015	1.119	0.907
Life Science	0.918	1.107	0.830
Advanced Manuf. Sys.	1.183	1.221	0.969
Earth & Environment	1.115	1.153	0.967
Total sample	1.129	1.153	0.980

Geometric mean of individual scores, 3 outliers excluded

The fastest growing departments are in this case Medicine and Energy & Transportation, which in the last period have displayed a higher growth in bad outputs in order to sustain their funds. Also the Cultural Identity and Agriculture & Food departments have improved their position thanks to intensive good/bad outputs production.

3.6 Conclusions and final remarks

The present work shows the situation of the Italian National Council of Research which, as a consequence of ordinary fund cutting, produces a portfolio of outputs that perfectly represents the multifaceted nature of science. Nevertheless, research outputs are not always evaluated as *good* because their scientific quality is questioned. This fine, and not always easy, distinction has been more and more relevant because the production of *bad* outputs has increased over time in relation to the more significant weight of external funds. However, the evaluation system of researchers and CNR research institutes has not changed even though researchers have had to revise and change their research vision and outputs to obtain external commitments and related revenues. Indeed, general efforts are concentrated on a subset of outputs able to give higher returns in terms of external and internal status. Ignoring this aspect of current research activity might lead to a biased representation of reality.

The recent internal reorganisation of CNR and numerous government initiatives aimed at reducing budgets have caused a sort of crowding-out effect, as underlined by Coccia and Rolfo (2008). The consequence is a reallocation of scientific efforts to more applied work, normally linked to specific external projects, which has a cost in terms of pure scientific outputs. In a regime of limited human and financial resources, this is the inevitable flip side of the coin. However, it is not a zero sum game: the Total Factor Productivity is increasing over the considered period and the need of becoming attractive on the research market seems to have a positive effect on efficiency. Our results underline something new compared to previous literature, which does not consider the whole scientific production. Kao and Hung (2008) find that departments operating in Medicine are the least efficient; on the contrary, Advanced Manufacturing System activities are the most productive. Sarrico (2009) concludes that considering only ISI articles in Portugal, Natural Sciences (corresponding to the CNR's Life Science and Molecular Design departments) are the largest contributors of publications, rather than Human and Social Sciences (corresponding to CNR's Cultural Identity and Cultural Heritage).

The results about the Italian CNR suggest that, considering a more complete set of scientific outputs and not only refereed articles in top journals, the efficiency ranking of Cultural Identity increases. A possible explanation is the strong fund cuts imposed on this department. Indeed, thanks to a structure slimmer than that of hard sciences (e.g. laboratories, machines and so on), the research institutes of the Cultural Identity department are more able to maintain their output level under a more stringent financial regime. Furthermore, considering only scientific research outputs, there still are wide margins for getting better. If all institutes were able to combine human and financial resources efficiently, *good* outputs would increase by around 25 %.

However, the main contribution of this study is about policy implications which could be extended to more general cases where the impact of financial constraints on scientific research activities is strong. Indeed, internal restructuring and reforms have modified objectives and incentive systems in many universities and research bodies especially in industrialised countries.

In our case, a higher level of integration between the Italian CNR and economic actors is required by the government, but the internal evaluation process is not geared towards these new features. Firms and other institutions ask for more applied work, often investigating local problems by using confidential data. These research outputs cannot be used to publish in top international journals, but they are essential for the survival of the institutes. Then, what is the mission of the CNR institutes? What should be the vision of the CNR researchers? Florida (1999) and Salter *et al.* (2000) affirm that the research system should stimulate talents and not technologies and then it would be necessary to establish a new equilibrium between patenting and research activity (Nelson, 2002).

At present, the trade-off between publishing and attracting external funds leads to a major paradox: researchers must publish to improve their career, but institutes ask them to follow external projects that only in a few cases allow them to publish good quality articles. In this new perspective, the CNR should read the presented results and rethink the evaluation systems of both research institutes and researchers, who should not be put in the situation of having to choose between improving their personal career and becoming consultants with a market-oriented vision.

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Chapter 4

Eco-efficiency and TFP growth across Europe: the case of chemical industry in Italy and Germany

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Abstract

This paper analyses the eco-efficiency of a sample of firms located in Italy and Germany, which are included in the European Pollution Emission and Transfer Register (E-PRTR). The Directional Distance Function (DDF) approach is here applied to obtain global efficiency score and TFP growth indexes, both able to consider pollution in computations. Standard Malmquist-Luendberg indicators are replaced by their sequential version to obtain more reliable results. Emissions generally increase between 2004 and 2007, with a worse performance of Italian firms. Eco-efficiency indicators partially slim down that evidence considering both turnover and input usage, underlining a reduction of average inefficiencies over time. From a dynamic viewpoint empirical findings shows a most favourable trends in environmental TFP growth for German firms. Finally a formal test for the Porter's hypothesis is provided, but its inconsistency emerges from the analysed sample when pollution is considered.

JEL classification: D24, O33, Q50, Q52
Keywords: Environmental Efficiency, Porter's Hypothesis, Chemical industry

4.1 Introduction

Environmental protection is nowadays a key point to be considered in all the industrial process, but in some cases it became one of the most important objective to be pursued by managers. New costs are imposed in order to respect regulatory constraint and they are so pervasive to influence at 360 degree all economical considerations regarding production decisions. In the case of mature industries, where margins are small and competitors numerous, new rules are the most powerful engine to stimulate green innovations and new investments (Fukasaku, 2005). Porter (1991) supposes the existence of win-win opportunities in the increasing stringency of environmental regulation, starting with the case of Japanese industry, able to grow more than US under more stringent rules. Costs of compliance will be offset by costs reduction from technological innovation encouraged by new standards and new obligations introduced (Porter and Van der Linde, 1995). Regulation could force new investments which embed technological progress, leading to a faster productivity growth and new profitable opportunities. European Community during last decades is becoming one of the most important and active decision makers regarding environment: a set of rules is adopted, in order to guarantee an homogeneous level of life quality in all the member states. One of the most important action in this direction was the adoption of the so called IPPC (Integrated Pollution Prevention and Control) approach. This consist in a common regulation framework (directive, regulation or decision) with the aim of protecting environment and reducing emissions, stimulating technical innovation in some relevant sectors. The directive 1996/61/EC and the EC regulation 166/2006 create a system of preventive authorisation to pollute that could be obtained after the adoption of the so called BAT (Best Available Technique) to reduce emissions. Another important point was the creation of a public register, in the wake of US Toxic Release Inventory published in the late 80s, now called European Pollution Release and Transfer Register (E-PRTR) after the inclusion of pollutant transfer activity in 2006. This strategy correspond to the so called *third wave* of environmental policies based on reputation or better *information disclosure*, after a first phase of *command-control* methods corresponding to pollution standards and a second *market-based* step, when tradable permits and emission fees were the main instruments (Canon-de-Francia *et al.*, 2008). Some doubts arise around the effectiveness of environmental reputation and in fact information availability by public register stimulate green performances if and only if data are effectively considered by public opinion and if green preferences are real in consumer choice (Caplam, 2003). Of course the adoption of BATs, which represent just an average environmental performances and also derives from a benefit-cost analysis, needs increasing investments on pollution abatement equipment, but also change in input-output mix, pollution prevention activity and process re-organisation. IPPC framework could then have different initial costs across industries and countries as well as among firms. Some primitive comparisons of regulatory costs have been proposed in order to understand the impact of the IPPC related policy REACH for new member states (Angherer *et al.*, 2008), but only basing the analysis on direct abatement activity. Across Europe coexist different levels of environmental sensibility: traditionally, in Germany the informal pressure on polluting firms to green innovations is high, also thanks to the presence of strong green parties and higher sensibility of social society (Rio Gonzales, 2009). In southern countries, like Italy, this aspects are weaker, especially regarding some industrial sites placed in less developed areas. Among the nine industrial sectors subject to the IPPC normative, the chemical industry is probably the most important and is traditionally associated to dangerous emissions, both in air and water. It also plays a key role as an intermediate manufacturer for all other industrial sectors and it has all the characteristics of a mature industry. Europe is the first chemical producer with around the 25% of the total world production, and in this scenario, Germany and Italy are respectively the first and the third producers (Federchimica, 2010). Firms located in this two countries have common features with their national industrial structure, but also significant differences in term average firm's size (Vitali, 2010). The adoption of a common set of standards can open important way to compare the economical and ecological performances of firms which must fulfil the same formal rule, but operating in different countries. Some interesting regional differences can arise between the two economical system (Fleishman *et al.*, 2009). The informal regulation is proved to be a significant factor enhancing environmental performances in manufacturing (Cole *et al.*, 2005) and the two economies traditionally show a different sensibility to the environment. All previous consideration makes the chemical sector a perfect candidate where to observe a dynamic in line with Porter's predictions if they are really valid, especially if productivity is interpreted in an extensive way to also consider pollution reduction. The long run debate on the inclusion of undesirable outputs in efficiency and productivity estimates was positively sorted out with the concept of Directional Distance Function (DDF), introduced by Chambers *et al.* (1996) at theoretical level. The power of the tool lies in the possibility to modify the direction in which to search for the efficient counterpart of each firms enveloping the more stringent idea of input or output distance function. Many application arise especially in the environmental field both with micro and macro economical perspective. Environmentally sensitive frontiers are derived in many cases of firms operating in different sectors or countries, mainly considering greenhouse gas emissions. Stating with DDF concept, also the estimation of itertemporal frontiers, able to consider also pollution reductions, became a common feature. Without prices information, not available for undesirable outputs, the Malmquist-Luenberger (ML) indexes are widely applied to estimate more reliable and global TFP growth indexes. All the computations are built on the DDF assumptions and Empirical application are numerous both at firm and aggregate level. Chung *et al.* (1997) is the first application of ML estimate analyse a sample of pulp and paper firms operating in US, Weber and Domazlicky (2001) analyse the manufacturing sector in US including air pollution, Arocena and Waddams Price (2002) apply ML to the electricity generation sector in Spain, Nakano and Managi (2008) do the same for Japanese firms, Barros (2008) propose a ML estimation for hydroelectric generators in Portugal and finally Yu *et al.* (2008) estimates TFP growth in the air transportation sector considering noise as undesirable output. The most ecent application of ML indexes are mainly focused on macroeconomical trends. The main examples, recent and less recent, are the following: Färe *et al.* (2001) about manufacturing sectors in US, Domazlicky and Weber (2004) on chemical 3-digit sectors, Yörük and Zaim (2005) on OECD countries, Kumar (2006) to a group of countries, Kortelainen (2008) to UE member states, Zhou *et al.* (2010) to most polluting countries in term of greenhouse gas emissions, Kumar and Managi (2010a) estimates EKC on the basis of ML growth indexes and finally Zhang *et al.* (2011) to Chinese provincial regions. In this kind of application as well as in standard application of Malmquist indexes is not uncommon to observe a decomposition of the overall TFP growth in efficiency recovery and pure technical progress. From a theoretical and methodological viewpoint it is very difficult to justify technical regress, easily observed in empirical estimates in many previous cited papers, both in ML and standard Malmquist framework. In classical DEA a sequential concept of technology is introduced by Tulkens and Vander Eeckaut (1995) regarding standard technology assumption and radial distance in order to avoid implausible downward shift of the technical frontier. For an extensive discussion of sequential technology concept see Shestalova (2003) who also propose a comparison among standard Malmquist values and decomposition in respect to the sequential approach. Oh and Hesmati (2010) propose the first extension of sequential technology estimates to the directional distance function framework. This paper proposes similar methodological tools to deal with the widely discussed relationship existing among eco-efficiency, regulation and TFP growth, starting with the well known statement by Porter. Its formulation is of course very generic and many interpretation arise in the literature, from the investigation on the relationship between regulation and innovation or R and D investments (Jaffe and Palmer, 1997) or capital stock age (Hamamoto, 2006), to the existence of competitive advantages for regulated firms (Mulatu, 2004). In the field of efficiency and productivity analysis Porter's hypothesis is mainly investigated in a standard settings, where undesirable outputs are not properly considered. Regulatory stringency indicator or measures of compliance cost, a proxy of firms' ability to react to regulation (Yarime, 2003), are analysed to test for positive correlation with efficiency. Murty and Kumar (2003), after creating an index of compliance for manufacturing firms in India, find a significant positive correlation with technical efficiency estimated through a parametric translog distance function. Another approach is followed by van der Vlist *et al.* (2007) in Dutch horticulture, by creating three dummy variables indicating three different stages of environmental regulation. They find a positive correlation among regulatory stringency and technical efficiency estimated through a parametric Cobb-Douglass production function. The interesting provide evidence fails in the measurement of productivity by considering only good outputs production in highly regulated sectors, where the reduction of environmental footprint is a key issue. In this sense the more rigorous work by Domazlicky and Weber (2004) test for consistency of win-win opportunities after estimating more reliable DDF efficiency score and Malmquist-Luenberger indexes. Results on the relationship between regulatory costs and productivity growth, conceptually more rigorous but based on macro-economical data about three digit US chemical industry, underline an insignificant correlation from which the validity of Porter's hypothesis is rejected.

The aim of the article is to provide, after applying a reliable estimation method, a set of eco-efficiency estimates for a group of firms located in Italy and Germany operating in the well identified sector of base chemicals. The existing relationship between productivity and regulation is then investigated to formally test the validity of the Porter's hypothesis. The existence and the impact of an informal or cultural pressure, specific for each country, is also tested among the determinants of the TFP changes. The remainder of this paper is organised as follows: section 4.2 briefly review the related literature, section 4.3 formally presents the model, database's issues are explained in section 4.4 and empirical results are summarised in section 4.5. This analysis is briefly concluded in section 4.6.

4.2 Eco-efficiency: the directional distance function approach

4.2.1 Theoretical framework

A fully non parametric and deterministic framework is here adopted since the estimation of shadow prices is not a priority. The main advantages rely in not having to assume before a particular functional form of DDF: estimates are then free from misspecification problems. From the other hand stochastic noise is ignored and all the observed departure from the frontier is detected as inefficiency. In this section the main characteristics of a production process with undesirable outputs are formalised on the basis of a commonly accepted axiomatic framework. First of all undesirable are a sort of byproduct results, then a positive production of good output is not compatible with a zero production of them. Secondly reducing bad outputs with unchanged input bundles is only possible, from a technological perspective, by reducing good outputs volume.
Some notation have to be introduced in order to clarify the points, let $x = (x_1, ..., x_N) \in R^N_+$ be a vector of inputs, $y = (y_1, ..., y_M) \in R^M_+$ a vector of good outputs and $b = (b_1, ..., b_J) \in R^J_+$ a vector of bad outputs. The output set $P(x)$ collects all the combinations of good and bad outputs that could be produced using each particular input vector x.

$$P(x) = \{(y, b) : x \quad \text{can produce} \quad (y, b)\}, x \in R^N_+. \tag{4.1}$$

Following Färe *et al.* (2007) the base chemical production process could be represented through some standard axioms satisfied by a generic polluting technology.

1. *Inactivity*. From a technical point of view the choose of remaining inactive is always possible. Then $0 \in P(x), \forall x \in R^N_+$.

2. *Compactness*. $P(x)$ is compact, then for each finite input mix x one could obtain a finite couple of vector (y, b).

3. *Free disposability of inputs*. As in standard technology representation, an increasing quantity of inputs allows to produce a fixed quantity of outputs. Inputs are freely disposable: $P(x) \subseteq P(x')$ if $x' \geq x$, or a Decision Making Units (DMU) could always obtain the same amount of outputs by implying more inputs and this is technically feasible.

These standard assumptions are always valid in modelling a production process. In presence of undesirable outputs one have to formalise the joint production idea and the cost of reducing, then two additional axioms need to be introduced:

4. *Null jointness*. It is impossible to observe positive amount of good outputs without observing also a positive amount of bad outputs, or in formulae

$$(y,b) \in P(x) \text{ and } b = 0 \Longrightarrow y = 0 \tag{4.2}$$

5. *Weak disposability assumption on outputs*. Each couple of vectors (y, b) is assumed to be weakly disposable, then they cannot be freely reduced:

$$(y,b) \in P(x) \text{ and } 0 \leq \alpha \leq 1 \Longrightarrow (\alpha y, \alpha b) \in P(x). \tag{4.3}$$

   In words only proportional contraction of both good and bad outputs are feasible (Färe *et al.*, 1989), because the decrease on bad outputs could only be performed by reducing desirable outputs if one consider inputs as fixed. Free disposability is still valid on the subset of good outputs for which every reduction is technically feasible without costs and maintaining inputs constant.

$$(y,b) \in P(x) \text{ and } y' \leq y \Longrightarrow (y', b) \in P(x) \tag{4.4}$$

The Directional Output Distance Function model (DODF), defined on the output set that meets previous axioms, gives the maximum feasible expansion of outputs in a pre-assigned direction maintaining inputs unchanged. The asymmetrical treatment of good and bad outputs is ensured by an appropriate choose of the directional vector (Chambers *et al.*, 1998): $g = (y, -b)$ as is done in the wide majority of papers dealing with DDF, in order to get a β of immediate meaning. The objective is to reach a model able to discredit base chemical firms which increase pollution and to credit them for reductions; also each increase in good outputs have to improve measured efficiency. DDF allows to search for the efficient counterpart of each firms along non-radial projections, the DODF value represents the maximum feasible expansion of the outputs vector. DODF takes a value equal to 0 for efficient DMUs and increase with inefficiency. Its formal definition is given by the following expression:

$$\overrightarrow{D}_O^W(x, y, b; g_y, g_b) = \max\{\beta : (y, b) + (\beta g_y, \beta g_b) \in P(x)\} \tag{4.5}$$

where $g = (g_y, g_b)$ is the directional vector and $g_y \in R_+^M$, $g_b \in R_+^J$. The particular directional vector comes directly out from IPPC directive: a continuous reduction in bad outputs production have to be achieved in order to obtain authorisation to pollute, from the other hand managers want to increase good outputs.

4.2.2 Contemporaneous and sequential ML indexes

Following the results on sequential technology introduced by Tulkens and Vanden Eeckaut (1995) and the extension in the environmental field by Oh and Heshmati (2010) standard Malmquist-Luenberger indexes of TFP growth could be restated assuming a more reliable definition of technology based on a sequential view. The basic assumption is that in each t all previous technological choices are still available. Describing the same concept, Shestalova (2003) concludes that the frontier at one time envelops all data points observed up to that time, eliminating by construction the problem of implausible downward frontier shifts sometimes obtained in empirical works. Starting with the contemporaneous output set assumed in standard ML setting:

$$P^t(x^t) = \{(y^t, b^t) \mid x^t \text{ can produce } (y^t, b^t)\}, \text{ with } t = 1, ...T$$

To assume a sequential idea of technology, it is sufficient to take the superset of each single contemporaneous production possibility set defined over the five previous axioms.

$$P^t(x^t) = P^1(x^1) \bigcup P^2(x^2) \bigcup .. \bigcup P^t(x^t)$$

Changing the definition of technology, standard ML indexes could be re-defined on that sequential output set to obtain a sequential version of ML, named SML. The two formulation are very similar the big S in each distance components recalls the fact that each distances is computed assuming the aforementioned sequential output set.

$$SML_t^{t+1} = \Big[\frac{(1 + \overrightarrow{D}_S^t(x^t, y^t, b^t; g^t))}{(1 + \overrightarrow{D}_S^t(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1}))} \cdot \frac{(1 + \overrightarrow{D}_S^{t+1}(x^t, y^t, b^t; g^t))}{(1 + \overrightarrow{D}_S^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1}))}\Big]^{\frac{1}{2}}$$

The ML index is built as the geometrical mean of two components - one based on technology at time *t* and one based on technology at time *t+1* - which represent the ratio of the DODFs calculated on quantities at time *t* and *t+1*. In the same manner SML is the geometric mean of two distances ratios, but the reference technology envelop all previous observations. An $SML = 1$ indicate an absence of productivity growth between t and $t + 1$, an increasing productivity emerges in case of $SML > 1$, the converse indicate a deterioration in the firms' position. One of the main advantages of sequential approach rely in a more robust definition of the frontier, in a way less sensible to extemporaneous or implausible observations.The TFP might be divided in two parts: the former representing the efficiency gain over the time period (*EFF*), the latter accounting for technical progress in the production function of chemical products (*TECH*):

$$EFF_t^{t+1} = \frac{1 + \overrightarrow{D}_S^t(x^t, y^t, b^t; g^t)}{1 + \overrightarrow{D}_S^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1})}$$

Given the assumption on sequential technology, the problem of implausible downward frontier shifts disappears, through a re-shaping implied by a different outputs set. An efficiency component $EFF > 1$ shows a catching-up process based on technological diffusion and imitation: the observed distance from the frontier is decreasing over time indicating an increasing homogeneity of performances. Of course the reference piecewise linear frontier could change over time and this effect if picked by the other term.

$$TECH_t^{t+1} = \Big[\frac{(1 + \overrightarrow{D}_S^{t+1}(x^t, y^t, b^t; g^t))}{(1 + \overrightarrow{D}_S^t(x^t, y^t, b^t; g^t))} \cdot \frac{(1 + \overrightarrow{D}_S^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1}))}{(1 + \overrightarrow{D}_S^t(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1}))}\Big]^{\frac{1}{2}}$$

The technical progress represents the share of TFP growth connected with new opportunities emerging from innovations. Short time periods are less easily interested by important technological shocks, then this component has limited impact often overcame by more reliable efficiency recovery. In general $ML_{t,t+1} \neq SML_{t,t+1}$ due the different outputs set on which they are estimated, but if technology is well defined along all the periods without exceptions, ML and SML are equivalent.

$$P^t(x^t) \subset P^{t+1}(x^{t+1}) \forall t \quad \rightarrow \quad ML_{t,t+1} = SML_{t,t+1}$$

4.2.3 Computation of distances and regulatory impacts

All the required distances to obtain and decompose SML indexes should be obtained, in a deterministic settings, through the solution of 4 linear programs for each firm. Two of them involve only contemporaneous output sets a t and $t + 1$, the other two explore sequential features.

$$\begin{aligned} \overrightarrow{D}_S^t(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1}) &= \max \beta \\ Y_t^\tau z^\tau &\geq y_{t+1}^k + \beta y_{t+1}^k \\ B_t^\tau z^\tau &= b_{t+1}^k - \beta b_{t+1}^k \\ X_t^\tau z^\tau &\leq x_{t+1}^k \\ z_k^\tau \geq 0, k = 1, ..K, \tau &= 1, ...t \end{aligned} \tag{4.6}$$

$$\begin{aligned} \overrightarrow{D}_S^{t+1}(x^t, y^t, b^t; g_y^t, g_b^t) &= \max \beta \\ Y_{t+1}^\tau z^\tau &\geq y_t^k + \beta y_t^k, \\ B_{t+1}^\tau z^\tau &= b_t^k - \beta b_t^k, \\ X_{t+1}^\tau z^\tau &\leq x_t^k \\ z_k^\tau \geq 0, k = 1, ..K, \tau &= 1, ...t + 1 \end{aligned} \tag{4.7}$$

Return to scale are assumed to be constant as it is done in the majority of environmental application of DDF, especially when intertemporal frontier have to be estimated: reliable TFP growth estimates could be derived only in case of CRS (Färe and Grosskopf, 1996). The equality constraint applied on bad outputs reveals the weak disposability assumption and influence both efficiency levels and potential TFP growth. In the present work both the case of regulated and unregulated scenario are considered, getting estimates of regulatory constraints from the comparison of efficiency score obtained by firms under the hypothesis of weak and free disposability of bad outputs. Following Picazo-Tadeo and Prior (2009) the difference in the estimated DDF for each firm under the two set of assumption could be used as a proxy of the cost to comply to environmental rules:

$$RI = \overrightarrow{D}_0^F(x^k, y^k, b^k; y^k) - \overrightarrow{D}_0^W(x^k, y^k, b^k; y^k)$$

Where superscripts F and W indicate respectively Free and Weak disposability on bad outputs. From a computational viewpoint, the equality in the linear programs relative to bad outputs are replaced by inequalities with the same direction of good outputs constraints. Of course assuming free disposability on bad outputs, is equivalent to exclude them from computation, then also affecting TFP dynamics. Both efficiency recovery and technical progress may change in an unclear way: literature on TFP growth often compare ML indexes with standard Malmquist, but there is no clear evidence on the bias direction. The previous literature underlines how theoretically both-sign biases are consistent with the model when bad outputs are missing. However, previous empirical findings, such Chung *et al.* (1997) or Weber and Domazlicky (2001), often reveal a negative bias on the estimated TFP growth if bad outputs are ignored. The situation is still more uncertain around SML. Here a simple way to compare results is presented, focusing on the observed role for each component in determining final differences.

$$(1 - \frac{SML^F_{t,t+1}}{SML^W_{t,t+1}}) = (1 - \frac{EFF^F_{t,t+1}}{EFF^W_{t,t+1}}) + (1 - \frac{TECH^F_{t,t+1}}{TECH^W_{t,t+1}})$$

Decomposing each index by subtracting 1, the total variation between SML under weak and free disposability of pollution could be seen as algebraic summation of the change in the efficiency recovery and technical progress under the two assumptions. Positive sign for components indicate an upward bias under free disposability, negative observations show an underestimated effect.

4.3 Data

Environmental data comes from the European Pollution Release and Transfer Register (E-PRTR), a public register published on-line by the European Environment Agency (EEA). This steps is part of the so called *third wave* of environmental regulation(Cañon-de-Francia *et al.* 2008) that is based on information disclosure. An European Pollution and Emission register is introduced with directive 1996/61/EC, but it became real only after 2000; with the regulation 166/2006 EC its application has been enlarged and also transfer activity is traced. E-PRTR is relatively young in comparison with US the Toxic Release Inventory born in 1986 and then it is still less investigated. All firms operating in 9 particular sectors must declare emissions if a double thresholds, on production capacity and emissions level, is overcome. In this paper only data for firms included in the point number 4, Chemical industry, are used. A certain homogeneity in firms activities is directly guaranteed by law: regulation CE 166/2006 provides a list of equipment and production capacity included in the register. Of course no information are provided about the share of that activities on the global turnover, but thanks to big dimensions required for each equipment, one could assume a significant contribute in total firm's production.

Table 4.1 shows in detail each specific activity for which emission are available in the chemical sector. General information, release means (air, water or soil), methods of measurement, particular installation and emission quantities must be declared in E-PRTR. The level of information is very fine: data must be delivered for each production plant and for each of 91 chemicals that are listed in the directive. Data release starts with 2001 observation, then 2004 and the last available is 2007. This last 2 data are here used and all emissions coming from air, water and soil are considered, but after an aggregation procedure to avoid convergence problems in computations of LP.

Firstly emissions from each plants are aggregated by firm, then they are summed up over release means using the following weighting scheme derived by the UE normative. For each substance the law assign a threshold, specific for each release means, that if overcame create the obligation to declare pollution in the E-PRTR. Applying the idea of damage function (Färe *et al.*, 2007), the inverse of allowed thresholds is assumed as an indicator of the toxicity level relative to each substance (Cañon-de-Francia *et al.*, 2008). The implicit idea is that the higher is the threshold the lower is the associated dangerousness for public health. The resulting indicators of environmental impact are computed for each release means and then summed in a global indicator. In notation:

$$b_k = \sum_{j=1}^{3} \sum_{g=1}^{91} d_{gj} q_{gj}$$

where $d_g = \frac{1}{T_g}$, g indexes pollutants, j indexes release means, k indexes firms, T represents thresholds relative to each pollutant and q is the total quantity released. The approach of including composite indicators of health risk is already applied by Färe *et al.* (2006), where two human risk-adjusted indexes of pesticide leaching and runoff are used as bad outputs to be minimised in a deterministic linear model. Economical data come from Amadeus on-line database, by Bureau Van Djick, that collects balance-sheets of European firms which are forced to lay their accounts. Of course physical data on production and inputs are not available, then economical proxies are taken from balance sheets information. Good output is replaced by total production value (Y), given by the total turnover, net of inventory changes. Capital stock (K) is measured as the net value of tangible fixed asset included while Labour (L) is proxied by the total labour costs to partially include both quantity and quality of human resources. Intermediate goods (M) are obtained by the sum of raw material costs (net to inventory change) and costs of services. Table 4.2 shows descriptive statistics for inputs and outputs, all variable are expressed in Euros at con-

Table 4.1: Chemical activities considered(CE 166/2006)

4. Chemical industry
(a) Chemical installations for the production on an industrial scale of basic organic chemicals, such as: (i) Simple hydrocarbons (linear or cyclic, saturated or unsaturated, aliphatic or aromatic) (ii) Oxygen-containing hydrocarbons such as alcohols, aldehydes, ketones, carboxylic acids, esters, acetates, ethers,peroxides, epoxy resins (iii) Sulphurous hydrocarbons (iv) Nitrogenous hydrocarbons such as amines, amides, nitrous compounds, nitro compounds or nitrate compounds, nitriles, cyanates, isocyanates (v) Phosphorus-containing hydrocarbons (vi) Halogenic hydrocarbons (vii) Organometallic compounds (viii) Basic plastic materials (polymers, synthetic fibres and cellulose-based fibres) (ix) Synthetic rubbers (x) Dyes and pigments (xi) Surface-active agents and surfactants
(b) Chemical installations for the production on an industrial scale of basic inorganic chemicals, such as: (i) Gases, such as ammonia, chlorine or hydrogen chloride, fluorine or hydrogen fluoride carbon oxides, sulphur compounds, nitrogen oxides, hydrogen, sulphur dioxide, carbonyl chloride (ii) Acids, such as chromic acid, hydrofluoric acid, phosphoric acid, nitric acid, hydrochloric acid, sulphuric acid, oleum, sulphurous acids (iii) Bases, such as ammonium hydroxide, potassium hydroxide, sodium hydroxide (iv) Salts, such as ammonium chloride, potassium chlorate, potassium carbonate, sodium carbonate, perborate, silver nitrate (v) Non-metals, metal oxides or other inorganic compounds such as calcium carbide, silicon, silicon carbide
(c) Chemical installations for the production on an industrial scale of phosphorous-, nitrogen- or potassium-based fertilizers (simple or compound fertilisers)
(d) Chemical installations for the production on an industrial scale of basic plant health products and of biocides
(e) Installations using a chemical or biological process for the production on an industrial scale of basic pharmaceutical products
(f) Installations for the production on an industrial scale of explosives and pyrotechnic products

stant 2004 prices and deflated using sector specific deflators from OECD [1]. Differences

Table 4.2: Descriptive statistics of Input and Output variables (2007)

Variable	mean	min	max	sd
Inputs (1000s of euros 2004)				
Assets	119,236	51.7	1,401,390	247,045
Intermediate Goods	314,558	1,830.2	2,787,152	516,628
Labour costs	64,315	138.4	758,782	124,795
Good Output (1000s of euros, constant prices)				
Turnover	526,922	9,100.4	3,721,139	805,998
Bad Output (environmental impact index)				
EII	72.24	1.02	469.87	121.82

in prices levels among countries, which could be easily ignored in case of physical quantity, matters when values are considered, because the underlying real quantities can differ significantly. Germany and Italy are exactly in such situation: a PPP actualisation is applied here in addition to constant prices transformation of all variables[2]. Some problems arise for some individual data due to Mergers and Acquisition or transformation process, but to partially control for data inconsistency firms showing an abnormal growth rate on inputs and outputs are excluded[3]. Secondly are only considered firms with unchanged business name and complete balance sheet data in both period. Finally each firm must declare emission in both period: this condition is potentially very restrictive because it exclude all virtuous firms able to reduce emissions under the thresholds. The latter point is a possible, but unusual process and in many cases is related to dismissing plant, then adopted restrictions guarantee more reliable environmental and economical data. Given the difficulties to collect complete data from balance sheets and the numerous restriction the number of analysed firms is only 44[4], 23 from Italy and 21 from Germany. However the sample is able to represent more than 23 billion of total production, around 10% of the

[1]The Gross Output deflator is applied to Y, the intermediate input deflator is applied to actualise M and L, and the deflator for Gross Fixed Capital is used for K. All deflators are relative to manufacturing sector and data came from OECD Stan Database for Structural Analysis

[2]PPP indexes relative to 2004 and 2007 comes from OECD Stan

[3]This is the case of the biggest Italian produced of polymers and resins, Polimeri Europa SPA, part of the Eni Group, excluded by the analysis because only 2007 economical data are reliable. In the period 2004 and 2007 Polimeri Europa receive all profitable activities by Syndial and by other firms of Eni. In 2004 the financial situation reveal a transition phase where all human resources were already transferred to Polimeri Europa but not jet industrial activities. Then from 2004 and 2007 the firms show an increase of revenues from 5 million to around 7 billion, with a similar trend in fixed capital.

[4]Firms included in E-PRTR for which is possible to collect complete economical data are respectively 79 and 70 regarding 2004 and 2007, but only 44 are observed in both period.

whole chemical industry in Italy and Germany[5], but around the 20% of base chemicals[6] (Federchimica, 2010). Starting from the aim of the present study, focused on looking at the productivity trend in presence of bad outputs, the analysis is restricted to firms showing emissions in both the time periods. In this way data are also cleaned by mergers and acquisition problems, because in many cases the exit from E-PRTR is an outcome of a reorganisation phase that normally leads to a new name for the firm.

Observing the emission levels from each firms give an intuition of the attention payed by firms in protecting environment. Average and relative Environmental Impact Indicators are reported in table 4.3 and show an increase of pollution between 2004 and 2007, both in absolute and relative term. Italian firms, which initially declared less emissions than their German counterparts, give a negative image of their efforts in protecting environment, showing a strong increase in EII. Expanding production in a phase of growth imply an increase of pollution especially if the emission level is low mainly for an under-utilisation of equipment. The Italian picture looks similar: emissions observed in 2007 are in line with the turnover path, the opposite in respect to German firms able to simultaneously increasing production an limited pollution.

Table 4.3: Total and relative emission levels

	Average EII		EII / Turnover (mlns)	
	2004	2007	2004	2007
GERMANY	68.61	56.59	0.258	0.163
ITALY	44.96	86.53	0.307	0.985
Total Sample	56.2	72.2	0.284	0.593

The difficulties of Italy in protecting environment are clarified in the last two column of table 4.3 where a relative measure of environmental impact is computed. The level of declared emission per million of turnover is more than doubled over three years, without any changes in the reporting procedure. The observed path is totally due to Italian firms which increase threefold their index, despite a more limited increases of turnover. From the analysis of purely environmental performances German firms show more reliable efforts in limiting pollution, but this position could be reached at the expenses of total factor productivity. The estimation of DDF models and SML indexes try to answer at remaining open issues.

[5]The cumulative turnover of the sample is respectively 5 and 18 billion of Euros for Italy and Germany and the country production was in 2008 respectively 57 and 139 billion

[6]Base chemical represent 55% of the chemical sector

4.4 Empirical findings

4.4.1 Environmental efficiency results

The set of linear programs, both assuming weak and free disposability of pollution are written and solved using R. Computed efficiency score in the observed regulated scenario are reported in table 4.4, CRS are assumed according to linear programs in previous section. Before results interpretation, it should be underlined that efficiency is a relative concept and then what comes from estimation is the position of each firm in respect to the best of the sample in a specific time period. The mean efficiency values appear really different over the two time period considered: the distance from the frontier is higher in 2004 and decrease over time, highlighting strong recovery of eco-efficiency. The mean performances of Italian and German firms are similar in 2004 and also in 2007, non-parametric Kruscal-Wallis test rejects the hypothesis of differences between the two groups in both periods. Of course some small differences arises, but only in 2007: Italian firms appear to be more eco-efficient of theirs German counterpart. That evidence seems to contradict purely ecological performances reported in table 4.3, but estimated DDF values also consider inputs and good outputs in assessing scores. The values of β represent the feasible

Table 4.4: Computed efficiency scores β, weak disposability assumed

	2004			2007		
country	mean	sd	$Pr(\beta = 0)$	mean	sd	$Pr(\beta = 0)$
GERMANY	0.859	0.240	5%	0.259	0.259	28%
ITALY	0.853	0.263	4%	0.226	0.228	26%
Total sample	0.856	0.249	4.5%	0.242	0.241	27%

expansion of good output and reduction of bad outputs in each time periods. High average values for DDF suggest the coexistence of very heterogeneous firms: a limited number of eco-efficient firms drives the frontier probably thanks to their ability to anticipate regulation and reducing their emission or production capacity under legal limits. Also when free disposability on outputs is assumed conclusions on Italian firms position do not change. From one hand data gathering partially drives this point: when a firm invests for greener equipment and specialised labour force, a decrease in the value of both Assets and Labour costs is really unusual. Labour costs are higher in Germany, due to higher salary standards, but also investments in Pollution Abatement Control are probably higher. German firms could appear more inefficient due to an higher, but costly attention to environmental footprints; reading together table 4.3 and 4.4 gives exactly this picture. The higher general inefficiency level directly comes from the small probability of lying on the frontier in 2004 in respect to 2007, another way to say some firms very eco-efficient, corresponding to a First in Class situation, operate together with less advanced realities. The first introduction of E-PRTR was in 2001, not so far and probably some problem in the adoption of BAT still emerges in 2004. Wide margins for potential contemporaneous increases of turnover and joint contraction of undesirable outputs are underlined by average DDF values higher than 50%. During the three years period many opportunities are caught and the situation appears more homogeneous at the end. The average distance form the frontier decreases drastically, but good possibilities to enhance green performances still remain also in 2007. Also in this case turnover could be expanded and emission reduced of around 20% if the best technology is adopted by all the observed sample. A less restrictive view of Porter's hypothesis proposed by Murty and Kumar (2003), suggest that a decreasing eco-inefficiencies over time could be seen as a first generic evidence in support.

4.4.2 Productivity dynamics

Only comparing efficiency levels over time, on the basis of a not fixed frontier does not allow to infer about real path of growth, then SML indexes are estimated on the bases of theoretical steps depicted in previous section. Table 4.5 shows results for the 2 subgroup of interest and the whole sample, applying geometric mean instead of arithmetic, in line with the index nature of SML indicators. Values bigger than 1 indicate an observed TFP growth while an indicator smaller than 1 shows a regress in the level of observed TFP. Considering the path under weak disposability gives results more similar to purely ecological performances showed in table 4.3. Italian firms suffer a negative growth of global productivity around -1%, in line with increasing emissions. On the contrary German firms show a growth around 7% in three years, mainly driven by a catching-up effect, as it is showed by the substantial contribute of the EFF component of SML indexes. In Italy chemical firms are loosing efficiency during the period, while their performances are sustained by higher frontier swift compared with the German case. The total number of firms showing a negative TFP growth is 22 over the 2004-07, 13 from Italy and 9 from Germany. Computation of SML under the assumption of free disposability allows to derive conclusion about the effectiveness of productivity enhancement without considering pollution. A priory expectations suggest that if a firm invest more in green assets or greener inputs,

Table 4.5: Sequential Malmquist-Lunberger indexes under weak and free disposability

	Weak Disposability			Free Disposability		
	$SML^W_{t,t+1}$	$EFF^W_{t,t+1}$	$TECH^W_{t,t+1}$	$SML^F_{t,t+1}$	$EFF^F_{t,t+1}$	$TECH^F_{t,t+1}$
Italy	0.992	0.977	1.015	1.029	0.963	1.069
Germany	1.068	1.067	1.001	0.953	0.923	1.032
Total sample	1.028	1.019	1.008	0.992	0.943	1.052

observed capital and intermediate goods tend to increase with a negative effect on purely technical efficiency. From table 4.5 results partially confirm this view, with German firms that shows a TFP contraction $(0.953 < 1)$ over the period under the assumption of free disposability. At the opposite, Italian situation underline a limited attention to pollution as the faster productivity growth in case of an unregulated scenario suggest. In this case the small reduction of TFP encountered the second column became a 1% growth rate if emissions are ignored, moreover 23 firms show a positive TFP growth, 14 of them are from Italy. The main observation regards variability of observed SML indexes, when free disposability is assumed: the variance of computed indicator increase three times in respect to the regulated case. An increasing heterogeneity suggest how pollutant are heavily considered in production choices: potential TFP growth shows large fluctuation to support the coexistence of different levels of sensibility to pollution reduction.

Table 4.6 shows the magnitude of the difference between the two set of assumption by taking the ratio of SML indexes under free and weak disposability hypothesis subtracting 1. Positive sigh in the Δ indicate that the productivity growth is higher when free disposability is assumed. Non-parametric Mann-Whithney test and parametric matched pair test are performed on the ratios: the two set of estimated SML are considered different only if the hypothesis of equality to 1 is rejected. In the parametric version of the test, geometric mean are applied and thanks to ratios could be computed without losing information [7]. In the total sample and in the two subsamples, parametric and non parametric tests are performed in order to verify if SML are different under regulated and unregulated scenarios in the second part of table 4.6. The tests are run for each component of SML and they show high accordance in rejecting the hypothesis of equality only for the technical progress component. SML are not statistical different under the two hypothesis on bad outputs nor the efficient component (EFF) in which they could be decomposed. On the contrary the frontier shift component is different and it is reasonable: disposability

[7] In the case of geometric mean negative values are excluded by computation, given that the sample is unique, the matched procedure is based on differences, equal to zero under H_0. Here this hypothesis on differences is replaced by an hypothesis on a ratio, equal to 1 under H_0.

Table 4.6: Change in sequential TFP indexes due to regulation

	$\Delta_W^F SML$	$\Delta_W^F EFF$	$\Delta_W^F TECH$
Germany	-10.81%	-13.55%	3.17%
Italy	3.73%	-1.47%	5.28%
Total sample	-3.48%	-7.43%	4.27%
H_0: $INDEX_W = INDEX_F$			
Mann-Whitney U test	Not rejected	Not rejected	Rejected
Paired-sample T test	Not rejected	Not rejected	Rejected

assumption directly influences the output set and then frontier's shape. The magnitude of this effect is so small that in the end final computed SML does not change significantly.

4.4.3 Testing for Porter's validity

Adopting an extensive interpretation of the Porter's statement, a reduction in the DDF value between a period t and a period $t+1$ should be interpreted as an weak evidence in favour of it if the period is characterised by increasing of environmental protection. Taking such less restrictive vision, one can conclude that in the analysed sample win-win opportunities exist both in the German and Italian case. On the same idea are drawn conclusion by van der Vlist *et al.* (2007) who, after applying a stochastic frontier approach, the Porter's hypothesis is accepted because technical inefficiency is decreasing over a period of increasing stringency regulation. Moreover, observing DDF value under regulated and unregulated scenario, if the distance between the two frontier is decreasing over time, it is a good signal of the presence of win-win chances (Färe *et al.*, 2007). Domazlicky and Weber (2004), assuming a non-sequential definition on technology, propose a more formal test to verify the existence of win-win opportunities. They take the value of RI index at time t as a measure of the regulatory stringency for each observed firm. If the Porter hypothesis is verified, then regulation stimulate a faster TFP growth, one should observe a positive and significant correlation between Malmquist-Luenberger indexes and the initial loss in potential good output. Here a similar approach is applied, but ML indexes are replaced by SML indexes and a richer model is applied instead of a simple correlation test. Starting with estimated SML presented in previous section and given the fact that TFP dynamics are not so different in the regulated and unregulated scenario, two models are run, to test the validity of Porter's statement under both scenarios. All the elements included in the model are already presented, only a couple of explanatory variable need to be introduced. First of all are isolated the so-called *innovative* firms, applying the identification procedure proposed at macro-economic level by Oh and Heshmati (2010). The motivation is that these firms show very strange dynamics, mainly due to their particular position in respect to the frontier. They argue that an innovative country must be able to show a positive technical progress between t and $t + 1$, improvement in the capacity of generating GDP and reducing pollutant between t and $t + 1$ and they must lie on the frontier in $t + 1$. According to this criteria, but noticing that in empirical estimates no firms show a real capacity in increasing turnover and jointly reducing pollution between t and $t + 1$, is possible to re-state the condition in a less restrictive way. That evidence shows a deterioration in the market opportunities in $t + 1$ in respect to t, probably due to the general crisis of the chemical industry, where quantity is replaced by quality (Vitali, 2010). Of course the passage to high profile chemicals and the reduction of volumes, change some typical characteristics of the sector, needs higher investment in technology and human capital, from which could emerge a deterioration of TFP performances. However the conclusion of technical regress cannot be accepted and this is one of the main point to assume a sequential nature of technology. The sufficient condition to be innovative could be here reduced to a positive TECH component and a DDF value equal to 0 in $t + 1$. Just 2 firms could be identified as *innovative* assuming free disposability and only 1 under the more reliable weak disposability hypothesis; two dummies are created to isolate this effect. Secondly a dummy variable, indicating the nationality of firms, is created in order to test for significance of informal pressure on TFP trends. If German firms are really more willing to enhance environmental performances due to external pressure, the dummy ITALY should be significant and negative. Finally a limited set of individual characteristics are included as control variables. A measure of size, given by the log of the average annual turnover to catch dimensional effect and potential evidence of diminishing returns around productivity potential. Finally a measure of vertical dis-integration, obtained as the ratio of intermediate goods over turnover, is also included to control for different commercial structures and strategies[8].

Previous studies investigating determinants of TFP growth apply different econometric technique in order to get consistent coefficient's estimates. Nakano and Managi (2008) use a system GMM framework to solve serial correlation of Malmquist-Luendberg in-

[8]The Adelman index of integration given by the ratio of value added over turnover is the measure of vertical integration commonly accepted, but in this case value added cannot be computed without loosing at least 3 observations. It is also impossible to obtain it in an indirect way from EBIT because depreciation is loosed, then a rough but more correct indicator of vertical disintegration is chosen.

dexes, while Watanabe and Tanaka (2007) apply a censored Tobit model. Other studies dealing with environmental efficiency scores, introduce a second stage based on the econometric theory stated by Simar and Wilson (2007). In the present paper the estimation of just one TFP growth index for each firms simplifies things and OLS could be properly applied. Results of estimates are reported in table 4.7. In both the case, under free and weak disposability of outputs the model seems to fit well, R^2 is high for both formulation, but the small number of observations represent a serious limits: results need to be interpreted and extended with care. In the first model the variability of SML is more limited and this will cause some difficulties, in effect just two over five explanatory variable are statistically significant. Sign of coefficient are mainly in line with a priori expectations and results partially support a positive correlation of TFP growth rate and initial regulatory impact (RI). RI represent the potential good output loss due to environmental regulation enabling to freely disposing pollution. Only if emissions are ignored in the production process Porter's statement is verified, because only in this case the coefficient is statistically significant. That evidence is manly in line with previous studies:

Table 4.7: Formal test for Porter's hypothesis

	Dependent variable	
Explanatory var.	$SML^W_{t,t+1}$	$SML^F_{t,t+1}$
RI_{2004}	0.00299	0.0280*
	(0.00450)	(0.0141)
IT	-0.0360	0.312**
	(0.0470)	(0.147)
INN^W	0.690***	—
	(0.0926)	(—)
INN^F	—	3.088***
	(—)	(0.406)
$SIZE$	-0.00479	0.0743
	(0.0158)	(0.0492)
VERT. DISINT.	0.455***	1.121**
	(0.161)	(0.512)
Constant	0.817***	-0.786
	(0.236)	(0.737)
Observations	44	44
Adj R^2	0.606	0.615

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

classical TFP estimates increase with the initial regulatory burden imposed on each firm.

However where a more complete definition of productivity is adopted, the presence of win-win opportunities disappears. Dummies isolating innovative firms are significant in both models with an expected positive sign, suggesting that their productivity growth is faster. The other important contribute comes from the control for the degree of vertical dis-integration. The higher is the share of intermediate goods over turnover, the higher is the TFP trend, confirming that outsourcing is a good strategy to boost productivity from an environmental and economical viewpoint. Dimension seems not to be an important factor in explaining SML indexes and the hypothesis of diminishing return remain un-accepted in the chemical sector. Similarly the idea of country level informal pressure on firm to enhance environmental sustainability cannot be accepted from the analysed sample because the dummy ITALY does not influence SML when pollution is considered. From the other hand, after controlling for other characteristics, being an Italian firms seems to be correlated with an higher TFP growth, but only in a classical unregulated framework.

4.5 Conclusion and discussion

This paper is probably the first attempt to investigate eco-efficiency assessment at international level, using productivity indexes corrected for the presence of pollution. Directional distance function approach, a well known methodology to get reliable global efficiency indicators, has been applied to a sample of Italian and German firms operating in very specific field, the base chemical sectors, for the period 2004-2007. Emission data, coming from the European register E-PRTR, are aggregated in order to create a global index of environmental impact used as bad output in efficiency computation based on a deterministic linear programming. Two eco-efficient frontiers are obtained for the two observation years and through the application of sequential Malmquist-Luenberger, reliable TFP growth indexes are calculated for all analysed firms in both period. Comparing the obtained estimates with outcomes of an hypothetical unregulated situation, a rough proxy of regulation implicit costs is derived. The results show that the efficiency scores are not so different between Italian and German firms, partially overturning the evidence from emission analysis. For both the groups average inefficiency strongly decrease from 2004 to 2007, identifying the imitation effect as the stronger component of TFP growth. In term of productivity growth German firms shows a better performance in comparison with their Italian counterpart, allowing to reduce significantly their impact on environment. Furthermore a formal test for the Porter's hypothesis validity is proposed, starting with results on sequential ML indexes. In the analysed sample, mainly composed by large base chemical firms operating in a classical mature industry, a priory expectation on the existence of win-win opportunities from environmental regulation, are partially disappointed. The initial regulatory burden, a measure of the specific impact of environmental protection on each observed firm, does not appear to be correlated with successive global productivity growth. However if emission levels are excluded by TFP growth computation an evidence in line with Porter's statement emerges. Another interesting point coming from empirical evidence is the role of outsourcing as a mean to sustain both economical and environmental performances of firms operating in mature industries. This aspect could open new research opportunities, but a deeper investigation on the role of dirty activity relocation is needed. Finally, something about the quality of used data need to be said. International comparability of emission data is sometimes poor and also at national level some problem arises also for internal comparability. This paper takes emission data from the same register and data meets OECD criteria for international comparability. Of course the sample dimension remains a clear problem that cannot be solved without costly international programs of direct data gathering.

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