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Greta Falavigna, Alessandro Manello

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The influence of financial and technological structure on eco-efficiency: an application of DDF bootstrapped framework in the Italian polluting industries

Greta Falavigna*

Research Institute on Sustainable Economic Growth (IRCrES),
National Research Council (CNR), Italy
Email: greta.falavigna@ircres.cnr.it
*Corresponding author

Alessandro Manello

Department of Economics, Social Studies,
Applied Mathematics and Statistics,
University of Turin, Italy
Email: alessandro.manello@unito.it
and
Research Institute on Sustainable Economic Growth (IRCrES),
National Research Council (CNR), Italy

Abstract: In this paper, we estimate environmental corrected efficiency scores for a large sample of Italian firms operating in four different polluting industrial sectors subjected to the same European normative framework. Merging economic and emission data coming from reliable public sources, we measure overall performances through the non-parametric directional distance function and in order to improve the robustness of the results, we perform an extension of the bootstrap proposed for standard efficiency scores. Results are analysed through a truncated regression after testing for the validity of separability condition between input-output space and explanatory variables as well as in light of industrial specificity. Results show that both the financial structure and the technological status of the firms have a significant explanatory power in relation to environmental corrected efficiency scores. Policymakers should carefully consider both aspects as important issues for supporting sustainable practices.

Keywords: environmental corrected efficiency; directional distance function; DDF; bootstrapping; two-stage procedure; separability conditions.

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Biographical notes: Greta Falavigna holds a Master's in Economics, PhD in Economics and Technology Management and Bachelor's in Literature. He is a senior researcher of the Research Institute for Sustainable Economic Growth (IRCrES) of Italian National Council of Research (CNR). Her main research

areas include econometric techniques and complex systems (i.e., artificial neural networks, genetic algorithm, decision trees, fuzzy systems, hybrid complex models, and so on) applied to different fields: finance, evaluation of firms' performance from economic and financial point of view, evaluation of public research, healthcare evaluation and judicial system. She has previously published her works in various scholarly outlets such as *Expert Systems with Applications*, *European Journal of Operational Research*, *International Review of Economics*, *Health Care Management Science*, *Health Policy*, *Agricultural Systems*, *Annals of Emergency Department*, *Research Evaluation*, *Socio-economic Planning Science*, *Scientometrics*, as well as *Journal of Small Business Management*.

Alessandro Manello holds a Master's in Economics and PhD in Economics and Technology Management. He is a researcher of the Department of Economics, Social Studies, Applied Mathematics and Statistics, University of Turin. His main research areas include efficiency, productivity and econometrics analysis. He has previously published his works in various scholarly outlets such as *European Journal of Operational Research*, *Scientometrics*, *Transportation Research Part E*, *Journal of Purchasing and Supply Management*, *Health Care Management Science*, *Agricultural Systems*, *Research Evaluation*, *Industrial and Corporate Change*, as well as *Regional Studies*.

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1 Introduction and literature review

The issues of environmental protection and sustainability of industrial activities are receiving growing attention all over the world and in Europe, the focus is mostly on the green performance of production processes through environmental regulations which are becoming increasingly stringent. The recent introduction and subsequent modifications of the so-called Integrated Pollution Prevention and Control (IPPC) Directive have created a set of restrictive obligations for firms, while the number of production activities involved has increased. Many firms are forced to measure, control, and reduce their emission levels to prove to the regulators that their processes incorporate the so-called best available technology (BAT) to limit environmental damage. In all developed countries, public opinion is becoming increasingly opposed to polluting industrial sites, and stakeholders and consumers are paying more and more attention to green performance indicators. Furthermore, entrepreneurs and managers try to implement environmental efficiency as a strategic choice. The result is a growing demand for scientific research aimed at creating productivity indexes or, more generally, performance measures that take into account both economic and environmental aspects of firm behaviour. The lack of information on the costs of pollution abatement stimulates the efficiency literature, both non-parametric and parametric, to deal with this issue. Since the contribution by Färe et al. (1989), which proposes a hyperbolic efficiency measure adding nonlinear constraints to standard data envelopment analysis (DEA), there have been numerous applications. Zhou et al. (2008) collect more than 100 environmental applications using linear programming methods or DEA, while Scheel (2001) focuses on the limits and properties of the main proposed extensions. The parametric literature deals with undesirable outputs by adding nonlinear constraints to output sets and by estimating hyperbolic efficiency via stochastic methods (Zofio and Prieto, 2001; Ball et al., 2004; Cuesta and Zofio, 2005), while the asymmetric treatment of good and bad represent remains more problematic within non-parametric models. To penalise firms that increase their emissions, the radial concept of distance has to be replaced with a more flexible estimator, which in this paper is the directional distance function (DDF). Introduced by Chambers et al. (1996, 1998), its power lies in the possibility of modifying the direction in which to search for the efficient counterpart of each firm, without changing the definition of technology. The second main difference in comparison to standard DEA estimator relies in the different assumption on the output set in order to represent a process where bad outputs are obtained as byproduct of the good output production. The DDF is characterised by additivity, which makes it possible to adopt a standard linear programming procedure, without assumptions about the functional form of technology. The applications of non-parametric models to environmental issues are growing across sectors and with different focus on the main results. A first stream of applied researches is confined to US micro-data on very specific sectors like for instance paper and pulp mills (Chung et al., 1997), glass plants (Boyd et al., 2002), public transport firms (McMullen and Noh, 2007), thermal power plants (Färe et al., 2007; Kumar and Managi, 2010a). A second set of works applies non-parametric models at aggregate or regional level, focusing on, for example, US regions (Macpherson et al., 2010), world countries in general (Kumar and Managi, 2010b), Chinese provinces (Zhang et al., 2011), Italian provinces (Falavigna et al. 2013) or the UK regions (Halkos and Tzeremes, 2013).

The last bulk of literature analyse micro-level firm data across Europe, analysing ceramic plants (Picazo-Tadeo et al., 2005; Picazo-Tadeo and Prior, 2009), olive farms (Picazo-Tadeo et al., 2011), cement plants (Riccardi et al., 2012), airports (Martini et al., 2013), chemical firms (Manello, 2017) and citrus farms (Beltrán-Esteve et al., 2017). We refer to Zhang and Choi (2014) for a complete review.

As literature clearly shows the application of environmental corrected efficiency model is normally confined to firms operating certain fine-grained industry level to guarantee homogeneous activities and homogeneous regulatory frameworks on the emission side. In Europe, the introduction of the IPPC regulations (Directives 1996/61/EC, 2008/1/EC) imposes that firms, operating in different polluting industries, prove the adoption of the so-called best available technology (BAT) in order to reduce their emissions and obtain pollution allowances. This creates a common regulatory framework for all firms operating within nine sectors if the certain production quantity and production capacity thresholds have been exceeded. Firms operating under the IPPC regime also have the obligation to measure and declare their emissions, with fine information at plant level on many pollutants and on their toxicity. A key issue concerns the identification of BATs which represent standard good environmental practices able to clearly contain emissions at accessible costs for both existing and new installations.

First-in-class technologies are just a subset of BATs; hence, it makes sense to compare all firms with them.

The IPPC framework creates the opportunity of analysing environmental corrected efficiency performance for larger samples and for groups of firms operating in different sectors, helping to slightly generalise results.

Indeed, this paper analyses a large sample of Italian firms operating in four different manufacturing sectors, under the same environmental regulation, and contributes to the literature in several ways.

First, we propose one of the most up-to-date approaches for computing DDF in a semi-parametric framework, where a bootstrap, based on results of Chernick (2011) and Simar and Wilson (1998, 2007), has been applied to reduce the bias of purely deterministic efficiency scores.

Second, we perform our analysis collecting data for firms operating in different industries, all subjected to the same environmental regulatory framework, the so-called IPPC regime. Our contribution is one of the first in this sense, and tries to extend the recent approach by Wang et al. (2018)[1] applied to a sample of highly energy-demanding firms operating in different sectors to a sample of firms operating in four different manufacturing sectors under a common regulatory framework.

Finally, following the most recent developments in efficiency studies, we use the computed efficiency scores as dependent variable for investigating some potential determinants of the obtained results. We adopt the most up-to-date approach, the truncated regression suggested by Simar and Wilson (2007), making an important step forward (i.e., the use of Algorithm 2) in comparison with previous works combining DDF-efficiency and regression analysis (see for example, Kumar, 2006; Watanabe and Tanaka, 2007; Nakano and Managi, 2008; Martini et al., 2013; Bruno and Manello, 2015). Moreover, we incorporate, here, the most recent results on the separability conditions the fundamental issues for the validity of regression results raised by Simar and Wilson (2011) and successfully solved by Daraio et al. (2018) for the standard DEA estimator. The paper is organised as follows: the production model, the bootstrap and the regression phase are presented in Section 2, the database and its related issues are described in Section 3, while the empirical results and tests are discussed in Section 4 with their main implication. Our analysis is then briefly concluded by Section 5.

2 Methodology

2.1 Modelling the environmental sustainability of production: the DDF approach

Each firm, operating in one of the five manufacturing sectors included in the IPPC regime, is assumed to combine a vector of inputs $x = (x_1, \dots, x_D) \in R_+^D$ in order to obtain a vector of good outputs $y = (y_1, \dots, y_M) \in R_+^M$ and simultaneously a vector of bad outputs $b = (b_1, \dots, b_J) \in R_+^J$, i.e., emissions. The output set $P(x)$ consists of combinations of good and bad outputs, which can be produced using the input vector x.

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

As outlined by Färe et al. (2007), environmental technology displays some properties of standard production theory, such as *inactivity*, *compactness*, and *free disposability of inputs*, but some specific features of bad outputs need to be considered. To model the idea that pollution is a byproduct, produced jointly with good outputs, and that reducing it is costly, Färe et al. (1989) propose two additional axioms: *null jointness* and *weak disposability of outputs*. The first assume that positive amounts of good outputs cannot be obtained without positive amounts of pollution, more formally $(y, b) \in P(x)$ and $b = 0 \Rightarrow y = 0$. The second assumes that undesirable outputs cannot be reduced for free and only proportional reductions in both good and bad outputs are feasible, because a decrease in bad outputs can only be achieved through a proportional reduction of desirable outputs, more formally, $(y, b) \in P(x)$ and $0 \leq \alpha \leq 1 \Rightarrow (\alpha y, \alpha b) \in P(x)$. In other words, weak disposability is a proxy of the behavioural limitations of firms in a regulated environment, where firms are forced by the law to consider and to reduce bad outputs production. This assumption, even if is very common in the literature, appears to be controversial in certain contexts: many authors highlight potential violation of the materials balance principle creating issues in term of convexity on the output set. However, Hampf and Rødseth (2015) to which we refer for a deeper discussion on this point, suggests that weak disposable models fit real technology properties if abatement activities are present, the same activities undertaken by firms within the IPPC regime which have to prove the adoption of BATs before operating. Moreover, according to the work by Podinovski and Kuosmanen (2011), the DDF estimator combined with the directional vector $g = (y, -b)$ lead to a production model that appear to be convex at least on its output sets for any level of inputs, as also recently highlighted by Dakpo et al. (2016). Standard free disposability remains valid for the subset of good outputs for which reductions are still technically feasible without costs, then

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

The DDF, defined on the output set built according to the previous axioms, measures the maximum feasible expansion of outputs in a pre-assigned direction, while keeping inputs unchanged. DDF value represents the distance of each firms with a best practice frontier, build using real observations of first-in-class technologies; a value equal to 0 indicates full efficiency (i.e., the firm contributes to the frontier), and it increases with inefficiency. We refer to Färe and Grosskopf (2000) for a deeper discussion on theoretical property, while Chung et al. (1997) presents the first application to the environmental context. The formal definition of the DDF estimator is the following:

$$D_0^W(x, y, b; g_y, g_b) = \max\{\beta : (y, b) + (\beta g_y, \beta g_b) \in P(x)\}$$

where $g = (g_y, g_b)$ is the directional vector and $g_y \in R_+^M, g_b \in R_+^J$. Thanks to an appropriate direction, which the choice is arbitrary, the model penalises most polluting firms by treating outputs asymmetrically. In literature, one of the most common directional vectors is $g = (y, -b)$ a direction scaled on firm-specific output bundles that gives scale-free βs that can be easily compared across firms. Moreover, in our case, this choice is perfectly coherent with manager's objectives[2] (i.e., maximising production) and with regulatory purposes (i.e., limiting pollution), but also on previous works using similar data (Manello, 2017). According to the non-parametric framework, directional distances have been computed by solving linear programs, one for each firm, according to the following formalisation:

$$D_0^W\left(x^{k'}, y^{k'}, b^{k'}; y^{k'}, -b^{k'}\right) = \max \beta$$

s.t.

$$x_{dk'} \geq \sum_{k=1}^{K} z_k x_{dk}, \quad d = 1, \ldots, D$$

$$(1+\beta) y_{mk'} \leq \sum_{k=1}^{K} z_k y_{mk}, \quad m = 1, \ldots, M$$

$$(1-\beta) b_{jk'} = \sum_{k=1}^{K} z_k b_{jk}, \quad j = 1, \ldots, J$$

$$z_k \geq 0$$

The obtained scores vary between 0 to + infinity, where 0 is assigned to firms that are on the frontier (i.e., efficient observation).

Returns to scale are assumed to be constant (CRS assumption hereafter), but when measuring economic/environmental efficiency, this point remains still controversial as highlighted by Picazo-Tadeo et al. (2012). Our motivations behind this choice are conceptual (i.e., relative to the production process we are describing), empirical (i.e., related to our specific data structure) and strategic (i.e., strictly related to our empirical strategy).[3] The CRS assumption is more general, and since the effect of dimension contributes to the efficiency scores, allows reasoning also with respect to this effect, that also policy maker should consider. In addition, as explained in Section 3.1, CRS allow to obtain more robust results.

Moreover, we decide to test the validity of the CRS assumption with reference to our specific data following the most established procedure available in the literature and Simar and Wilson (2002, 2008) on VRS and CRS DEA estimators incorporating pollutants.[4] Finally, in light of the conceptual and empirical consistency of the CRS assumption, we decide to maintain first stage efficiency estimates as simpler as possible[5] for the increasing complexity of next phases (i.e., bootstrap and truncated regressions).

2.2 *The bootstrap procedure*

In order to improve the robustness of results, a bootstrap methodology also to the DDF technique has been applied. Simar and Wilson (1998, 2007) referring to the non-parametric models, show that bootstrapped scores perform well, in particular when the two stage approach is applied, as in the present analysis [i.e., Algorithm 2 (Simar and Wilson, 2007)]. Bootstrap procedure is a mathematical methodology that allows replicating *N* random sub-samples, starting from the initial dataset. The main result of bootstrapping is a correction of DDF estimates with a bias term computed following suggestions of Simar and Wilson (1998, 2007) for non-parametric approach. In details, the bootstrap procedure consists in generating *N* random sub-samples with replacement starting from the initial one. In this case, an observation of the initial sample can be replicated more times in the same sub-sample because the replacement option is set. For each sub-sample, the DDF score of each DMU can be computed. If we denote $f = 1, \ldots, F$ where F represents the number of observations and $n = 1, \ldots, N$ where N is the number of replications, $\hat{\beta}_f^n(x, y, b)$ is the DDF score of the f^{th} DMU in the sub-sample n.

To simplify notations, let we consider $f = 1, \hat{\beta}(x, y, b)$ represents the DDF score obtained from the starting sample, $\hat{\beta}^{*1}(x, y, b), \ldots, \hat{\beta}^{*N}(x, y, b)$ are the DDF estimates calculated through the bootstrap procedure, then the bias term can be calculated as follows:

$$bias = \frac{\sum_{n=1}^{N} \hat{\beta}^{*n}(x, y, b)}{N} - \hat{\beta}(x, y, b) = \overline{\beta}^{*}(x, y, b) - \hat{\beta}(x, y, b).$$

This means that the bias for each observation is the difference between the mean value of bootstrapped estimates and the score obtained from the initial sample. Simar and Wilson (1998, 2007) suggest considering the DDF initial scores with the following correction:

$$\hat{\beta}^{*}(x, y, b) = \hat{\beta}(x, y, b) - bias = 2 \cdot \hat{\beta}(x, y, b) - \overline{\beta}^{*}(x, y, b).$$

2.3 Truncated regression and separability issues

Daraio and Simar (2007b) includes the DDF among the potential extensions for semi-parametric inference applied to standard DEA scores, an extension confirmed by more recent and specific contributions like Simar et al. (2012). In fact, the two data generating processes are very similar and strictly related in practice (except for the truncation point at 0 instead of 1); hence, it is plausible to assume that they have the same statistical properties. Some previous works on the DDF, like those by Watanabe and Tanaka (2007) or Blancard et al. (2006), apply a second stage model, but based on the Tobit model for censored data. Picazo-Tadeo et al. (2011) perform a truncated regression on an augmented DEA model that considered environmental issues. According to Simar and Wilson (2007), the standard estimation method based on the censored model might lead to misleading conclusions. Therefore, a truncated regression estimated via maximum likelihood should be always preferred. This framework has been extended to the DDF case by some recent contributions. Among the others, Martini et al. (2013) or Bruno and Manello (2015) perform a truncated regression on deterministic DDF scores (i.e., DDF computed without a bootstrap phase), while Falavigna et al. (2015) represents the first contribution that extend Algorithm 2 proposed by Simar and Wilson (2007) to the DDF case. Let us assume the following simple regression model:

$$\hat{\beta}_k^{*}(x, y, b) = \gamma' w_k + \alpha' z_k + \varepsilon_k \geq 0$$

where $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$ before truncation, w_k represents a set of firm-level controls which potentially affect eco-efficiency performance, while the main variables of interest (i.e., two dummies proxying the *financial dependence* and *innovation* level of the firms) are collected into z_k. The unknown eco-efficiency scores β_k, based on an unknown technological frontier, are estimated according to the DDF framework with bootstrap by

$\hat{\beta}_k^*(x, y, b)$ through a first stage analysis following the linear programs presented in Section 2.1. The main difference from a second stage analysis in the standard DEA approach is the truncation point: in the original version by Simar and Wilson (2007), the efficiency scores are bounded from below by unity, while here, under the DDF, they are bounded from below by zero. The assumption on ε_k remains the same before truncation, normal distribution with zero mean and unknown variance, but what changes is the truncation point imposed through the new condition $\varepsilon_k \geq -\hat{\gamma}' w_k - \hat{\alpha}' z_k$. The econometric model is then estimated via the maximum likelihood technique, by applying a truncated regression model, and to obtain a more reliable confidence interval, a bootstrap procedure is used also in the ML estimation of the truncated model. The sequence of actions as well as additional information all bootstrap phases can be find in Simar and Wilson (2007) or Simar et al. (2012), to which we refer for each technical issue.

Moreover, when interpreting regression results, Simar and Wilson (2011), Bâdin et al. (2012) and more recently Daraio et al. (2018) show that the application of the truncated regression is valid (i.e., estimated coefficients are meaningful) only if the separability condition between the input-output space and explanatory variables of eco-efficiency is valid. If the hypothesis on separability is rejected, the coefficients from the regression can be not correctly interpreted, and consequently the precision of estimates is weaker. As suggested by Devicienti et al. (2017), separability implies that external factors influence the production process only through the conditional density function (i.e., the probability of lying on the frontier, for any given level of external factors), without influencing its support as Daraio et al. (2018) explain. In their recent contribution, Daraio et al. (2018) propose a specific test on separability conditions that should be run before each regression phase on efficiency scores. In this study, the above-mentioned test has been applied in order to verify separability for the two qualitative aspects, which are the main object of interest in term of efficiency determinants. In general terms, the test proposed by Daraio et al. (2018) propose a comparison of efficiency scores computed in a standard setting versus efficiency scores computed in a conditional setting, where conditional variables are those entering as regressors in the truncated regression phase. If separability is valid, estimates from the two settings should not differ so much, and a normally distributed *t*-test can be used as in standard hypothesis testing. In our specific case, the test is simpler because we focus our attention on a couple of qualitative variables (i.e., at lease for the simpler regression model we use) that eliminate the issue of bandwidth optimisation, which is typical of more complicated conditional frameworks.

3 Data

3.1 The input-output space

Environmental data have been extracted from the European Pollutant Release and Transfer Register (E-PRTR). This public online register, published by the European Environment Agency (EEA), is part of the so-called *third wave* of environmental regulations based on information disclosure (Cañon-de-Francia et al., 2008). A European Pollution and Emission Register was introduced with Directive 1996/61/EC, but it was implemented only after 2000. Regulation 166/2006 EC extended its application and transfer activities were also traced. The E-PRTR is relatively young in comparison with the US Toxic Release Inventory, established in 1986; hence, it has not been widely investigated. All firms operating in nine specific sectors must declare their emissions if they exceed the thresholds for production capacity and emission levels. The information to be provided includes release media (air, water or land), methods of measurement and emission quantities. The report includes a large number of details, since specific data must be delivered for each plant and for each of the 91 chemicals listed in Regulation 166/2006, together with the thresholds under which no risks for health arise.

The present analysis considers only the following manufacturing sectors:[6] production and processing of metals (2), mineral industry (3), chemical industry (4), paper and wood (6) and other activities (9).[7] Some E-PRTR sectors are excluded due to their not strictly manufacturing nature, such as energy production (1) or waste management (5), or due to limited data availability, as in the case of livestock and aquaculture (7) or animal and vegetable products (8).

Air and water emissions are used in the present study because data on release to soil and water mainly overlap and data on soil emissions are often unavailable for the included sectors. Economic data come from the Bureau Van Djik's AIDA database, which collects the balance sheets of Italian firms obliged to lay their accounts. Both economic and environmental variables regard the year 2007, mainly because the last information of emission by E-PRTR is relative to 2007.[8] In the absence of physical data on production and given the heterogeneity of the sectors included in the analysis, an economic measure of good outputs is used. Among the balance sheet variables, following Pieri and Zaninotto (2013), total production value is represented by total turnover, net of inventory changes. However, authors considered the value added (VA), calculated as the total production value net of intermediate goods (i.e., the sum of raw material costs net of inventory changes and costs of services). Physical consumptions of energy and water cannot be included separately in efficiency computations, but are included among other raw materials and services in monetary values and directly reduce the VA produced, used as good output. Capital stock (K) is measured as the net value of both intangible and tangible fixed assets and labour (L) is proxied by total labour costs, trying to take the quantity and quality of human resources into account. All data are expressed in euros, and it is important to note that balance sheet data only represent proxies of real variables. The DEA models are created to work with physical quantities and to compare homogeneous production processes. In this case, monetary values are used to obtain input and output measures comparable among sectors; hence, the results must be carefully interpreted. In matching environmental and economic data, the emissions of different production plants must be integrated based on release media and firms. The data remain untreatable from a linear programming point of view, because specific pollutants are too numerous. Moreover, some substances are characteristic of specific sectors, then information on emissions is condensed by using a weighting sum based on the toxicity of each substance, following the idea of damage function proposed by Färe et al. (2006). Firms in the E-PRTR are not assumed to produce a physical quantity of pollution but rather to generate environmental damage, which has an impact on public health. Each DMU produces an impact on air and water measured by the weighted sum of the pollution quantities for both release media. Weights are directly derived from the E-PRTR regulations, assuming the inverses of the allowed thresholds as indicators of toxicity levels (Cañon-de-Francia et al., 2008). The underlying idea is that a higher threshold indicates a lower toxicity level, thus a smaller inverse to weight the related emissions produced. In notation:

$$b_k = \sum_{g=1}^{91} d_g q_{kg}$$

where $d_g = \frac{1}{T_g}$, g indexes pollutants, k indexes firms, T represents thresholds for each pollutant and q is the total quantity released. This operation is run separately for emission in air and into water, then the two resulting indicators collapsed into one *index of environmental impact* given by the sum of the two indicators. The approach is similar to that by Färe et al. (2006), where two human risk indexes for the toxicity of pesticides are used as bad outputs to be minimised in a semi-parametric model. Table 1 shows input and output data for all 159 firms, averaged based on their activity codes.

Table 1 Summary statistics by E-PRTR activity code, means and standard deviations

	E-PRTR activity code			
	2	*3*	*4*	*9*
Inputs (1,000,000 s euros)				
Tang. and intag. fixed assets	188.900	89.392	67.906	123.957
	(–443.738)	(–99.600)	(–156.352)	(–427.368)
Labour	61.087	25.902	30.940	55.203
	(–117.254)	(–27.323)	(–56.645)	(–189.559)
Desirable outputs (1,000,000 s euros)				
Value added	137.071	54.316	61.769	66.599
	(–257.189)	(–58.104)	(–111.771)	(–192.865)
Undesirable outputs (impact indicators)				
Air and water	126.428	20.699	206.375	48.633
	(–327.883)	(–32.818)	(–537.650)	(–157.561)
N	49	35	48	27

Notes: 2: metal industry, 3: cement, glass and ceramic industry, 4: chemical industry and 9: other manufacturing activities. Standard deviation in parentheses.

The observations regarding environmental impact on air and water provide some hints about the kind of production processes involved: metal and chemical industries are the most polluting in terms of air emissions, while waste waters are mainly released by other manufacturing firms collected in the last activity code which includes various types of production processes. Bad output introduced in the estimation of frontiers is the sum of these two impact indicators, while through the damage function framework problem of different unit of measure are solved. Given that we run separate DDF estimation for each sector involved in the analysis, dimensionality could represent a potential issue. We think on this point also according to the recent contribution by Wilson (2018) that highlights minimum sample sizes to use in non-parametric models. In our case, given our input-output space of four variables (two input, one output and one bad output), approximately 30 observations are needed in order to obtain meaningful estimates in case of CRS assumption[9], while this number is lower in case of VRS or FDH estimators (i.e., respectively 15 observations for VRS and 5 for FDH).

Finally, considering technical details and sample size, estimates from the DDF estimator under CRS assumption are the best choice, that allows to maintain industries separated during first-stage efficiency computation with bootstrap.[10]

3.2 Variables affecting environmental corrected efficiency in the truncated regression

In this section, we provide a complete list of the variables included in the regression phase, mostly of them based on recombination of financial statement data which are used to create structural indicators. The idea is that a variable can be used as explanatory if decision makers – managers in this case – cannot influence it during the period considered (Lovell, 1993). A less stringent interpretation of this concept allows including some explanatory variables that might be affected by managerial actions in each time-period but, given their long-term nature, cannot be strongly influenced in the short run.

First, we use environmental corrected efficiency scores computed considering four polluting technologies, one for each of the four sectors analysed. In the regression phase, we pool efficiency indicators computed from different contexts and then, we include industry dummies for neutralising structural differences among sectors. The E-PRTR activity codes are accurate and closely correspond to the Italian ATECO activity codes, which are more precise only for the chemical sector (4). In particular, base chemical industry (ATECO 20) and base pharmaceutical products (ATECO 21), both included in E-PRTR code (4), have been here separated. The underlying idea is that, after controlling for firm characteristics, which are sometimes peculiar to each sector and affect environmental performance, some differences among industries might persist. These will represent the intrinsic differences among production processes in complying with the same regulations. Hence, when policy makers decide to reduce the environmental impact of economic activities, some sectors will suffer more than others, due to the intrinsic characteristics of their technologies. Dummies for each activity are introduced and the heterogeneous activities included in E-PRTR code (9) are assumed as the control group.

Secondly, we control for some firm-specific characteristics which may potentially affect eco-efficiency performances. *Geographical location* should matter for two main reasons. On the one hand, firms located in the South of Italy may have fewer formal and ‘informal’ constraints (Cole et al., 2005) for differentiated perception around environmental problems. On the other hand, IPPC implementation and E-PRTR data gathering are delegated to regional governments, which are the authorities in charge of checking the authorisations to pollute and the adoption of BATs. Different institutional approaches and degrees of public awareness create different levels of pressure on firms in relation to the improvement of environmental performance. Moreover, general economic considerations might influence overall productivity and the gap between the North and the South of Italy cannot be ignored. Coherently, dummies corresponding to geographical macro-areas have been included into the regression.

The *age* of the firm could be another potential explanation of environmental sensibility as well as of performance in general. We analyse if young in comparison to older firms are more efficient in term of emissions with the idea that cultural factors can affect entrepreneur preferences to less polluting technologies. On the contrary, older firms probably can have more possibility to invest and also more experience in environmental protection. The variable *age* has been computed according to age of the firm in 2007, with reference to the year of its birth.

Regarding the *size* of the firm, several studies on technical efficiency suggest to control for the relationship between size and performance, both in solely economic-focused setting (Latruffe et al., 2008) and in environmental efficiency contexts (Picazo-Tadeo and Garcìa-Reche, 2007). In the present study, we expect that large firms will try to improve their green performance to achieve higher returns in terms of image and relationship with society. This aspect is particularly important for polluting sectors, since public opinion is always distrustful of large enterprises. Moreover, big firms might more easily take advantage from scale economies in controlling and measuring emissions, thus achieving cost savings. On the other hand, larger firms are characterised by higher emission levels and this might have a detrimental effect on their eco-efficiency. Three dummy variables has been introduced in order to control for *size* (i.e., medium, large firms and very large).[11]

The vertical extension of the firms could be a key-determinant of eco-efficiency performance, particularly when most polluting activities have been externalised. In the general, many studies focused on manufacturing sectors underline the positive relation between outsourcing and efficiency or productivity (Manello et al., 2016; Manello and Calabrese, 2017). Here, this aspect has been considered using the VA variable as good output of DDF model.

The financial situation of the firms could strongly influence both economic and environmental performance; we decide to deeply investigate this aspect under different sides of analysis. We compute *financial rating* scores, a compact judgement on financial risk of each enterprise, through the CerisRating software[12], introduced by Falavigna (2012) and based on artificial neural networks procedure applied to balance sheets data. Notice that bankruptcy assessment is a very relevant information for financial institution when firm applies for a loan. The obtained classification of firms corresponds to the classical letters-based definition of default risk that increases from AAA (i.e., low risk) to D (i.e., firm in bankruptcy). We condense rating information through a dummy variable, named *financial rating*, equal to 1 if the firm is low risk (i.e., is classified as AAA, AA and A), 0 otherwise.[13]

We compute also a *capital intensity* index for considering heterogeneous levels of fixed assets among industries and firms. This variable represents the inverse of the capital endowment needed to generate each unit of production. Similarly, Rose et al. (2004) use the sales/total assets ratio to study the environmental performance of the firms in S&P500, and they find a significant negative relation with emission levels, which suggests higher pollution levels for higher capital endowment. In our work, the numerator is represented by sales, while fixed assets are used instead of total assets to build the *capital intensity* variable.

Finally, we compute two key dichotomous variables that represent the main focus of our regression phase. We build an indicator of the financial capacity of firm: a proxy of the financial pressure on the firm, an aspect that, according to Nickell et al. (1997) may potentially influence performances. Self-financing capacity is a very important aspect: a firm heavily relying on external sources is not as free to invest in environmental protection, since banks are much more concerned about the ability to repay loans than about environmental issues. Hence, financial problems can be expected to have a negative effect on green choices related to efficiency. An index of *financial independence* from external funds is calculated for each k^{th} firm:

$$Financial\ independence = \frac{Net\ equity}{Total\ assets - depreciation\ of\ \ fixed\ assets\ \ fund}$$

We introduce this variable as a dummy (i.e., *financial independence*) with value equal to 0 if the indicator is lower than 0.7 (i.e., low financial independence), representing a situation of strong exposure with external financial institutions, and then a major default probability of financial default (AA.VV., 2002; Frattini, 2011). On the contrary, value of the dummy equal to 1 indicates high financial independence, and consequently, a lower bankruptcy risk.

The second key indicator represents a proxy of *innovation*. In general, internal or external acquisition of technology or innovation is positively related to technical efficiency. This is also the case of eco-efficiency indicators, as highlighted by Carrion-Flores and Innes (2010) that reports a negative correlation between the number of patents and emission levels. The lack of specific data about internal research efforts represents a major limit but, given the medium or large size of the firms considered in this analysis, some information on innovation can be drawn from their balance sheets. We use the capitalisation of some R&D expenses among assets as a proxy for the internal creation of technology. We create a dummy *innovation* that assumes the value 1 if the ratio between intangible assets and total fixed assets is greater than 0.1.

4 Results and discussion

4.1 Environmental efficiency: empirical evidence from DDF estimates

For each E-PRTR firm with complete data, environmental corrected efficiency scores are calculated by solving the linear programs in Section 2.1 with the application of the bias correction described in Section 2.2. All the programs are written and solved using R-statistics. Before interpreting the results, it should be emphasised that efficiency is a relative concept and each score represents the position of each firm in relation to the best firm in the sample for each analysed sector. Five separate frontiers are estimated on five output sets, which make possible to assume a homogeneous production process for each sub-sample. Even though inputs and outputs are designed to compare industries directly, a conservative approach is the best choice: the DDF model is estimated separately for each sector, so that the computed efficiency scores are robust in relation to structural differences among activities. Since the DEA models are mainly suited to comparing homogeneous firms, it would be inappropriate to draw frontiers using observations from plants operating in different sectors.

Notice that for each analysis, average values of efficiency scores without bootstrap $(\widehat{\beta})$ have been reported in order to estimate the Kruskall-Wallis test. Table 2 and following ones (Table 3, Table 4 and Table 5) present results of the Kruskal-Wallis non-parametric (Kruskal and Wallis, 1952; Wilcoxon, 1945, 1992) and parametric tests. In all presented analyses, rejecting the null hypothesis, findings suggest that biased efficiency scores ($\hat{\beta}^*(x, y, b)$, calculated through bootstrapping procedure) are on average bigger than those obtained without bootstrap ($\hat{\beta}(x, y, b)$). These results, confirmed by both parametric and non-parametric tests, suggest that if the bootstrap procedure is not applied, the inefficiency appears underestimated.

Table 2 shows the results of a regulated model, in which weak disposability is assumed for bad outputs. The value of the estimated DDF β represents the potential simultaneous increase in turnover and reduction in environmental impact deriving from the adoption of the best technologies in each sector. The first column shows small DDF values, suggesting a good level of environmental performance for all the analysed industries. The average estimated $\hat{\beta}^*(x, y, b)$ is around 0.620 for the whole sample, with poorer performance in chemicals ($\hat{\beta}^*(x, y, b) = 0.802$) and in metals ($\hat{\beta}^*(x, y, b) = 0.681$), and better performance in minerals ($\hat{\beta}^*(x, y, b) = 0.320$).

Table 2 Efficiency scores by industry

Industry		*Freq.*	$D_0^W(x, y, b; y, -b)$			*Param. test*	*Non-param. test*
			$\hat{\beta}^*$	*Pr(β = 0)*	$\hat{\beta}$		
2	Metals	49	0.681	12.2%	0.604	*Rej.****	*Rej.****
3	Minerals	35	0.319	25.7%	0.276	*Rej.****	*Rej.****
4	Chemicals	48	0.802	10.4%	0.742	*Rej.****	*Rej.****
9	Other	27	0.556	11.1%	0.444	*Rej.****	*Rej.***
Total		159	0.619	14.2%	0.546	*Rej.****	Rej***

Notes: 2: production and processing of metals, 3: mineral industry, 4: chemical industry and 9: other activities.
***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.

Following the IPPC principles, in order to operate on the market, each firm needs to prove that it has adopted the so-called BATs, but these merely represent an average environmental standard, which can be achieved at reasonable costs. Consequently, the estimated DDF scores might be interpreted as the distance between BATs and first-in-class technologies for each input-output mix. By adopting this point of view, it becomes easier to interpret the results for minerals, a sector that has always been heavily regulated, with constant increases in environmental protection. Therefore, the IPPC provisions require a higher level of protection, which fundamentally corresponds to implementing the most advanced technologies. Good environmental performance within the sample is also supported by a high probability of being on the efficient frontier, which is around 14% for the whole sample, with a peak of 26% for the mineral industry.

Results of tests shown in Table 2 confirm significant differences among sectors, thus eliminating the hypothesis of mean and median equality.

Table 3 shows results by firm size based on the European classification. Large firms seem to perform better than small and medium enterprises, but the evidence is stronger for very large firms, which display lower DDF scores representing a better level of environmental efficiency. The non-parametric and parametric tests also confirm statistical differences in performance among the various size groups. At the same time, very large enterprises ($\hat{\beta}^*(x, y, b) = 0.623$) are better at taking advantage of their economies of scale, while the small and medium enterprises show the worst performance $(\hat{\beta}^*(x, y, b) = 0.733)$. Interpreting the results from a policy perspective, the fact that the efficiency decreases as size increases suggests that the distance between BATs and best technologies is smaller for smaller firms. This highlights an important feature of the IPPC principles: they are more easily adopted by SME than by large or very large, which are both, on average, further away from the frontier. The second column shows the probability to be on the frontier, then to be efficient. Only the 11% of small and medium enterprises are on the efficient frontier; whereas the percentage increases to 17% considering large firms.

Table 3 Efficiency scores by dimensional class (European classification)

Size	*Freq.*	$D_0^W(x, y, b; y, -b)$			*Param. test*	*Non-param. test*
		$\hat{\beta}^*$	*Pr(β = 0)*	$\hat{\beta}$		
Medium	47	0.733	10.6%	0.652	*Rej.****	*Rej.****
Large	82	0.552	17.1%	0.552	*Rej.****	*Rej.****
Very large	30	0.623	13.3%	0.553	*Rej.****	*Rej.****

Notes: SMEs: revenues under 50 mlns. euros, large: revenues between 50 and 500 mlns. euros and very large: revenues over 500 mlns. euros.
***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.

Actually, SMEs are closer to the frontier, indeed the score starts from 0 (efficient) to plus infinite; however, the probability for large firms to be on the frontier is bigger than for SMEs.

This result suggests that for SMEs, the possibility to adopt new and more ecological technology, that allows increasing the efficiency, is bigger than for large firms that seem to have lower incentives to adopt the best technologies because they are already efficient. The bigger probability to be in the frontier for large firms suggests that these enterprises are less stimulated to innovate.

Considering tests, results suggest that also considering size of firms, the bootstrap procedure allows obtaining more realistic measures of inefficiency.

Table 4 Efficiency scores by macro-areas

Macro-areas	*Freq.*	$D_0^W(x, y, b; y, -b)$		*Param. test*	*Non-param. test*	*Total emissions*	*Sales to emissions index (mln. of €)*
		$\hat{\beta}^*$	$\hat{\beta}$				
North-West	86	0.706	0.630	*Rej.****	*Rej.****	13,407	5.19
North-East	34	0.486	0.412	*Rej.****	*Rej.****	2,986	4.91
Central Italy	20	0.582	0.525	*Rej.****	*Rej.***	3,990	3.05
South and Islands	19	0.501	0.430	*Rej.****	*Rej.****	499	19.24

Notes: North-West (Piedmont, Liguria, Valle d'Aosta, Lombardy), North-East (Veneto, Emilia-Romagna, Trentino Alto Adige, Friuli Venezia Giulia), Central Italy (Tuscany, Umbria, Marche, Lazio) and South and Islands (Basilicata, Campania, Abruzzo, Molise, Puglia, Calabria, Sicily, Sardinia).
***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.

Another relevant aspect is the geographical location, for which descriptive evidence is provided in Table 4, where data are grouped according to ISTAT macro-areas. Average efficiency scores show that the North-East is the best performing region $(\hat{\beta}^{*}(x, y, b) = 0.486)$ followed by the South and Islands $(\hat{\beta}^{*}(x, y, b) = 0.501)$ represented by only one firm. The column total emissions represent the sum of impact index (i.e., air and water) for each geographical macro-area. Considering average levels of sales to total emissions index, values in Table 4 shows the amount of sales obtained from a unit of emission. Values are expressed in millions of euros and show that in South and Islands there are firms with bigger sales for unit of emission, followed by North-West and North-East. In addition, also for geographical location, parametric and non-parametric tests confirm the relevance of the bias correction through bootstrap.

Finally, Table 5 presents descriptive statistics considering the default probability of firms and the efficiency scores computed with and without the bootstrap procedure. The probability to be on the frontier is bigger for healthy enterprises but notice that the number of firms with low rating judgements is very low. In this case, parametric and non-parametric tests have been computed considering a dichotomous variable considering firms with high and low rating. However, findings suggest an underestimate of inefficiency calculated through DDF without bootstrapping procedure.

Table 5 Efficiency scores by rating classes

Rating classes	*Freq.*	$D_0^W(x, y, b; y, -b)$			*Param. test*	*Non-param. test*
		$\hat{\beta}^{*}$	*Pr(β = 0)*	$\hat{\beta}$		
AAA	15	0.401	33.34%	0.335		
AA	58	0.580	17.24%	0.499		
A	35	0.590	14.29%	0.527		
BBB	22	0.796	0.00%	0.699		
BB	4	0.894	0.00%	0.864		
B	2	0.000	100.00%	0.000		
CCC	-	-	-	-		
D	-	-	-	-		
Financial rating good (AAA + AA + A)	108	0.558	18.52%	0.675	*Rej.****	*Rej.****
Financial rating poor (from D to BBB)	51	0.746	5.88%	0.485	*Rej.****	*Rej.****

Note: ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.

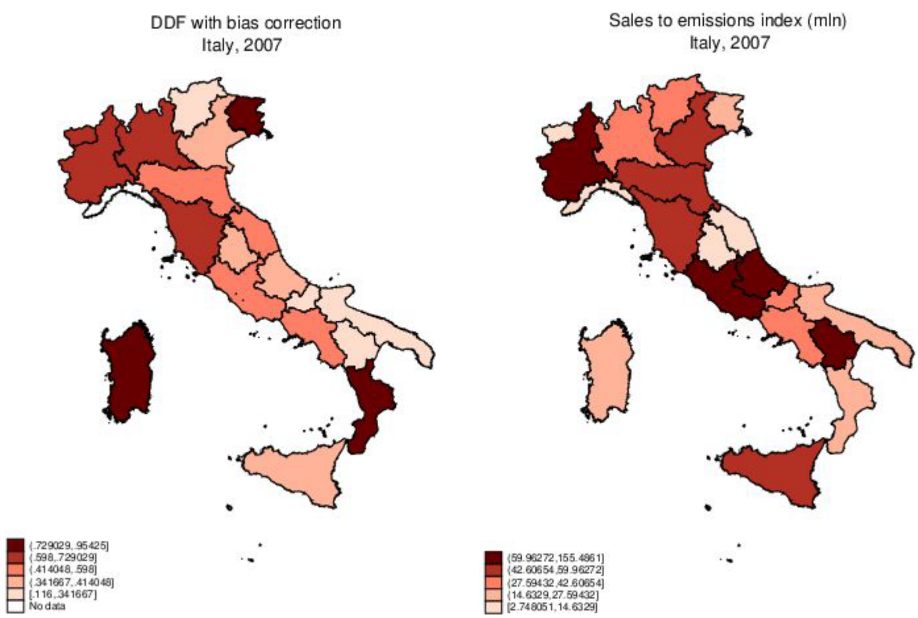
Results can be viewed also in Figure 1 where maps represent Italian regions shaded on the basis of the environmental efficiency scores [Figure 1(a)] and sales to emissions index [Figure 1(b)].

4.2 Determinants of environmental corrected inefficiency

After estimating bias corrected eco-efficiency scores, we investigate the relevance of a set of potential determinants, already presented in Section 3.2, of environmental and economic performance through the truncated regression model introduced in Section 2.3.

Following the list of potential extension of the second stage approach in Daraio and Simar (2007a, 2007b), we use bias corrected DDF efficiency scores as to replace DEA efficiency scores in the methodology proposed by Simar and Wilson (2007) through their Algorithm 2. Table 6 collects the results for the four estimated models, in which efficiency scores with bias correction always represent the dependent variables. The single-bootstrap procedure is applied to obtain lower and upper bounds for coefficient confidence intervals, assuming a non-standard distribution for them. Of course, the statistical inference is still based on deterministic efficiency scores; therefore, it cannot solve the problem of absence of noise related to frontier identification. The results are not the same as those of an econometric model, because inefficiency is not strictly a random variable: the outcome of inference only considers the sampling error.

Figure 1 Maps of Italian regions based on (a) environmental efficiency scores and (b) sales to emissions (see online version for colours)



(a) (b)

In details, column 1 considers separately the impact of *financial independence* variable; while the second (2) study the separate effect of *innovation* on environmental efficiency of firm. Notice that these issues have been tested for separability conditions (Table 7). The third column (3) presents results considering *financial independence* and *innovation* jointly, while the fourth formulation (4) adds to the previous variables two other characteristics of firms (i.e., *financial rating* and *capital intensity*). Moreover, as control variables, all models consider one general information (i.e., *age*) and three dummy variables on size, region and industry.

The information of financial position is represented in the model through the *financial independence* variable, that appears always significant in models (1), (3) and (4), with a negative sign (i.e., increasing *financial independence*, decreasing inefficiency). This perfectly agrees with theoretical background presented in Section 3.2. If the weight of financial debts decreases, also inefficiency decreases. More independent firms appear more efficient from an economic point of view, and at the same time, they are less affected by environmental protection regulations. Financial situation is determinant in the decision process of manager/producer because investors can have reservations about managerial strategies, especially if investments are risky. The financing of firms is affected by many factors, external and internal to corporate, and literature suggests that external investors, as banks, must be convinced about strategies of manager/producer, in particular if investment is in innovation (Hall, 2002; Coad et al., 2016; Mazzucato, 2013). Obtained results confirm that in-debt firms have the problem of financing technology investments; indeed, the efficiency decreases if the enterprise is able to produce using technology environmentally friendly and then, if manager/producer is able to collect capital for R&D expenses. However, these investments can be risky because the spillover effects are not immediately perceived by external investors. The signal effect deriving from the adoption of environmentally sustainable technology does not affect sales in the short-run. So, probably, investments and research and development activities in environmental technology are financed through social capital, and then firms independent from a financial point of view are more efficient.

Table 6 Second stage truncated regression for explaining eco-inefficiency levels (bootstrapped results)

Variables	*(1)*	*(2)*	*(3)*	*(4)*
	$\hat{\beta}^*$	$\hat{\beta}^*$	$\hat{\beta}^*$	$\hat{\beta}^*$
Financial independence^	–0.123*		–0.126**	–0.117*
	(0.063)		(0.063)	(0.063)
Innovation^		–0.093*	–0.096*	–0.104*
		(0.056)	(0.055)	(0.055)
Age	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Financial rating^				–0.061
				(0.047)
Capital intensity				0.000
				(0.000)
Size dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes
Constant	0.554***	0.558***	0.574***	0.601***
	(0.105)	(0.106)	(0.104)	(0.105)
Sigma	0.237***	0.238***	0.234***	0.232***
	(0.0156)	(0.0157)	(0.0154)	(0.0152)
Wald chi2	99.06	96.98	103.76	107.38
p > chi2	0.000	0.000	0.000	0.000
Sample	135	135	135	135

Notes: ^Dummy variable.
Standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.

The second column (2) presents results on *innovation* variable that shows negative significant relation in all models (2), (3) and (4). Indeed, investments in internal or external acquisition of technology also influence positively environmental and economic efficiency, playing a crucial role in reducing environmental corrected inefficiency. Firms investing in research or in buying licenses gain greater advantages in terms of efficiency, supporting the idea that, in these industries, innovation mostly focuses on pollution control.

After including together, the two main variables of interests, *financial independence* and *innovation* variables (column 3), and our results confirm previous findings, highlighting the robustness of hypotheses thought.

Last column 4 reports the most complete model specification, controlling for the effect of other variables on environmental efficiency. In particular, other two aspects (i.e., *financial rating* and *capital intensity*) have been added to the formulation of model, but results suggest that these variables show respectively negative and positive effect on environmental corrected efficiency. However, results remain statistically weak.

In order to test the robustness of obtained results, the same truncated regression model has been estimated taking non-bootstrapped efficiency coefficients into consideration. Results are reported in Table A1 in Appendix and they show the same conclusion, even if with a lower significant level.

In order to be really confident on the above-reported results, separability conditions should be tested and we applied the simplified test focused on our two main variables of interest, *financial dependence* and *innovation*. This test, conducted following Daraio et al. (2018), to which we refer for all technical details, is based on the idea of comparing unconditional and conditional efficiency scores, where the conditioning variables are the main regressors of interest. Conditional estimates consider the environmental variable one by one in the sampling procedure before the computation of the efficiency and under the null hypothesis unconditional and conditional efficiency scores are not so different. Indeed, the rejection of the null hypothesis means that separability is violated because scores computed in the unconditional setting diverge from those in the conditional setting. In this case, environmental variables affect the shape of the technology and results obtained in the second stage can be difficulty interpreted, with problems that resemble endogeneity. For this reason, a satisfying result of the test is to accept the null hypothesis meaning that the truncated regression phase is meaningful.

Table 7 collects the obtained results (i.e., the p-values) for the three identified cases (i.e., single variables one-by-one and the results from combining the two dummies of interest) and suggest that the null hypothesis can be accepted in all cases (i.e., single and joint test). Therefore, separability conditions are satisfied in our specific case, at least with reference to our main variables of interest and all the above-mentioned consideration on the second stage regression can be interpreted in the usual way.

Table 7 p-values for tests of separability on financial dependence and innovation variables

Environmental variables	$\hat{\beta}^*$	$\hat{\beta}$	*Freq.*
Financial dependence	0.1244	0.1100	159
Innovation	0.8303	0.9429	159
Joint test	0.8434	0.5526	159

Note: ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.

5 Conclusions and policy implications

This paper examines the relationship between technical efficiency and production of pollutants in some Italian industries in which environmental regulations are stringent. A semi-parametric directional output distance function is applied under the assumption of multiple bad outputs produced together with one desirable output. Differently from previous works, many pollutants are considered and aggregated according to their toxicity levels derived from the European legislation. Another insight presented in this paper is the comparison between estimates of environmental efficiency obtained with or without bootstrapping procedure. Results suggest that non-biased scores underestimate inefficiency, weakening related analyses. Environmental corrected efficiency scores are computed for each firm and the results are analysed from an innovative inter-industry perspective, however without disregarding microeconomic aspects. Moreover, it represents one of the first attempts at analysing efficiency scores through a two-stage procedure, using recent econometric results based on bootstrapping and separability conditions tests.

Once environmental corrected efficiency has been computed, firm-level scores have been analysed through a second stage phase, where the combination of bias corrected DDF efficiency scores and the application of a bootstrap phase around the truncated regression represents one of the first applications of the Simar and Wilson's (2007) Algorithm 2. We concentrate on two crucial aspects: internal or external innovation and financial dependence, both measured through dichotomous variables (i.e., *financial independence* and *innovation*). After testing for separability condition validity, limiting the focus on those two aspects, we can argue that *innovation* and *financial independence* positively influence eco-efficiency performances. Moreover, we verify the robustness of our findings by including many characteristics of firms as control variables according to different model specification and our conclusion remain unchanged.

Of course, many limits of deterministic approaches remain. The double bootstrap procedure applied increases the reliability of results, but the semi-parametric nature of the framework implies that noise is not contemplated in the frontier identification, and then the inference phase only considers sampling errors. In addition, further research can be done considering also external-environmental variables in the definition of the non-parametric frontier. Indeed, the separability conditions test if some variables can affect the frontier and but if these variables cannot be controlled by the manager/producer, they cannot be considered nor inputs nor outputs. Daraio and Simar (2007a) suggest of adopt conditional non-parametric frontier in order to consider directly in the model external environmental variables affecting the definition of the production function. In our study, we applied the separability conditions for two indexes representing a specific strategy of manager/producer. Indeed, financial and technological situations depend from decisions and strategies of manager/producer that surely considers the environmental context but this last does not affect directly the indexes proposed in the present work. An example of environmental external variable could be the presence of specific law in each analysed industry.

Nevertheless, the current analysis sheds light on important aspects of the environmental performance of polluting firms, their individual characteristics, but, most importantly, contributes to the debate on the potential policy instruments for fostering ecological performance of polluting firms. Even if all analysed manufacturing plants come from mature industries investing in innovation (internally or externally created) represents one of the main channels for sustaining environmental corrected efficiency. Therefore, policy or incentive scheme can lead to win-win opportunities able to sustain both economic and environmental performances. The result on financial independence is less straightforward. The introduction of more stringent environmental principles, by reducing firms' behavioural freedom, highlights the importance of a balanced financial situation for reacting to external shocks. External financial creditors are mainly focused on their short-term returns (i.e., the debit refund), while boosting environmental corrected efficiency requires long-term perspectives and strong investments. In case of financially dependent firms both aspects are partially in contrast with external financial sources and the reduction of pollution moves to the backgrounds. In this direction, all policies able to stimulate lower level of firm financial dependence may open new opportunities for eco-friendly practices.

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Notes

1 In this case, firms analysed operate in energy production, basic material manufacturing, public utilities and industry firms, but each sub-sample of firms is small and the efficiency analysis has been performed by pooling firms making different activities.

2 With our choice of the vector, we focus on the idea of positive adaptation (i.e., a firm increases its volume of desirable outputs and simultaneously decrease emissions). According to Dakpo et al. (2016), this can be achieved through some managerial effort such as the adoption of new technologies that can mitigate pollution. Of course, also if a firm is able only to expand good output, or contract emissions separately is more efficient than another firms which is static.

3 For a deeper discussion of returns to scale assumption, see Fukuyama (2003) and Picazo-Tadeo et al. (2012).

4 Test statistic applied on DEA estimates for different sectors are that proposed by Simar and Wilson (2002, 2008). In details, the bootstrapped version has been adopted and the null hypothesis is that production set is globally CRS. The *p*-values of test for each industry are: 0.7820 (for industry 2), 0.8825 (for industry 3), 0.7825 (for industry 4) and 0.9843 (for industry 9).

5 Indeed, the VRS assumption in combination with DDF estimator increase computation difficulties and lead to other controversial issues.

6 Activity codes from Regulation 166/2006 in parentheses.

7 This is a residual category comprising heterogeneous processes (such as leather tanning, textile dyeing and surface treatment using solvents).

8 Unfortunately, more recent updating of environmental data is not available.

9 Following Wilson (2018), considering industry 2, the sample allows to obtain robust results as a regression with 49 observations, for industry 3, results are robust as a regression with 35 observations, for industry 4, results are robust as a regression with 48 observations, and finally, for industry 9, results are robust as a regression with 27 observations.

10 A potential industry of interest included into the E-PRTR, paper and pulp industry (E-PRTR6) has been excluded by our analysis for the small number of observation available.

11 Medium: revenues under 50 mlns. euros, large: revenues between 50 and 500 mlns. euros and very large: revenues over 500 mlns. euros.

12 The validation of results is proofed on evaluation provided by Bureau van Dijk that provides balance sheets of Italian firms into the so-called ‘Aida database’. However, it contains comprehensive information on companies in Italy but also financial strength module with ratings, credit risk position and default probability from various expert providers.

13 Different letters correspond to different classes of default risk. In particular: AAA is assigned to firms with an extremely strong capacity to meet financial commitments. This is the highest score: AA means that firm has a very strong capacity to meet financial commitments, A: is awarded to enterprises with a strong capacity to meet financial commitments but somewhat susceptible to adverse economic conditions and changes circumstances, BBB indicates that firm has an adequate capacity to meet financial commitments, but more subject to adverse economic conditions, BB indicates that firm is less vulnerable in the near-term but faces major ongoing uncertainties to adverse business, financial and economic conditions, B: is assigned to enterprises more vulnerable to adverse business, financial and economic conditions but currently has the capacity to meet financial commitments, CCC represents the situation in which firm is currently vulnerable and dependent on favourable business, financial and economic conditions to meet financial commitments, and D indicates that firm is in bankruptcy.

Appendix

Table A1 Second stage truncated regression for explaining eco-inefficiency levels (non-bootstrapped results)

Variables	*(1)*	*(2)*	*(3)*	*(4)*
	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$
Financial independence^	–0.125**		–0.128**	–0.114*
	(0.063)		(0.061)	(0.060)
Innovation^		–0.130**	–0.132**	–0.144***
		(0.054)	(0.053)	(0.053)
Age	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Financial rating^				–0.090**
				(0.044)
Capital intensity				0.000
				(0.000)
Size dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes
Constant	0.375***	0.387***	0.404***	0.447***
	(0.105)	(0.104)	(0.102)	(0.101)
Sigma	0.229***	0.228***	0.223***	0.219***
	(0.0156)	(0.0154)	(0.0151)	(0.0147)
Wald chi2	103.10	105.26	113.09	122.86
p > chi2	0.000	0.000	0.000	0.000
Sample	135	135	135	135

Notes: ^Dummy variable.
Standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.