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Environmental regulation and green productivity growth: Evidence from Italian manufacturing industries

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Abstract:	Climate Action, as part of the seventeen goals of Sustainable Economic Development Plan, has become an important strategy for the United Nation countries; governments have correspondingly implemented various environmental regulation policies. However, few studies have discussed the impact of environmental regulation on productivity growth at industry level, and the empirical evidence is still controversial. Based on panel data from 1995 to 2017, this study analyzes the effect of environmental policies on productivity by measuring the adjusted productivity growth in thirteen Italian manufacturing industries using Malmquist-Luenberger index. The main result of this investigation is that environmental regulation does not have a negative impact in almost all industries. A bootstrapping approach has been used to assess the robustness of estimated results.
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UNIVERSITÀ POLITECNICA DELLE MARCHE

Dipartimento di Scienze Economiche e Sociali
DISES

Ancona, March 1st, 2022

Dear Editors,

we are pleased to submit our original research article on: "Environmental regulation and green productivity growth: Evidence from Italian manufacturing industries" for consideration in Technological Forecasting & Social Change.

In the paper, we analyze the effect of environmental policies on productivity by measuring the adjusted productivity growth at sectorial level using the Malmquist-Luenberger index. We use panel data from 1995 to 2017 for thirteen Italian manufacturing industries. The main and original finding of our research is that environmental regulation does not have a negative impact on productivity in all industries, except for the food and beverage sector.

This manuscript has not been published and is not under consideration for publication elsewhere, bears no conflicts of interest, and fits with your journal guidelines for submissions. Please address all correspondence concerning this manuscript to me at m.cucculelli@univpm.it

Thank you for your consideration.

Sincerely,

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Title Page with Author Information

Environmental regulation and green productivity growth: Evidence from Italian manufacturing industries.

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Abstract

Climate Action, as part of the seventeen goals of Sustainable Economic Development Plan, has become an important strategy for the United Nation countries; governments have correspondingly implemented various environmental regulation policies. However, few studies have discussed the impact of environmental regulation on productivity growth at industry level, and the empirical evidence is still controversial. Based on panel data from 1995 to 2017, this study analyzes the effect of environmental policies on productivity by measuring the adjusted productivity growth in thirteen Italian manufacturing industries using Malmquist-Luenberger index. The main result of this investigation is that environmental regulation does not have a negative impact in almost all industries. A bootstrapping approach has been then used to assess the robustness of estimated results.

Keywords: Environmental regulation, Productivity growth, Direction Distance Function, Malmquist-Luenberger index, manufacturing industry, Italy.

Jel classification: D24, O13, O44, Q56,

Short bio

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Daniela Lena is a PhD candidate in Economics at Università Politecnica delle Marche (Italy). Her main areas of interest are productivity study under environment regulation, innovation and business models. She is currently working on trade-off between environmental regulation and productivity, and novel business modeling design. She has published on *European Journal of Social Science Education and Research* and *Economia Marche-Journal of Applied Economics.*

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Carl Pasurka is an economist with the Economy and Environment Division, Office of Economy and Environment at the US Environmental Protection Agency. He received his PhD from the University of Illinois at Urbana-Champaign in 1981. He was an associate editor of the *Journal of Environmental Economics and Management* from 1994 through 1996. His current areas of research include environmental accounting and measuring the impact of pollution regulations on traditional and adjusted measures of productivity. His research has appeared in a variety of journals including the *Review of Economics and Statistics, Journal of Environmental Economics and Management*, *Review of Income and Wealth, and Economic Modelling*.

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Marco Cucculelli (PhD Rome) is professor of Applied Economics at Università Politecnica delle Marche (Italy) and director of the PhD in Economics. He is the Secretary General of the Italian Economic Association and Fulbright Distinguished Chair at the University of Pittsburgh (USA). He has published on the fields of innovation, corporate finance and entrepreneurship in *Research Policy*, *Journal of Corporate Finance*, *Small Business Economics*, *Journal of Evolutionary Economics*, *Cambridge J of Economics*, *Journal of Cleaner Production*, and other international journals. Marco is an Associate Editor of JSBM, JSBE and the *Italian Economic Journal.*

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Abstract

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Environmental regulation and green productivity growth: evidence from Italian manufacturing industries.

1. Introduction

This paper is related to the recent and growing international debate on trade-offs between economic growth and environmental protection policies undertaken by governments. Although numerous studies highlight the benefits environmental regulations provide to society in the form of improved environmental conditions and quality of life, concerns remain about how pollution abatement influences the economic viability of firms, industries, and countries. More stringent environmental regulations increase the production costs of firms which, in turn, could cause a loss of productivity and competitiveness. Different authors, like Knights et al. (2014), Hubian et al. (2018), and Herman and Shenk (2021), proved environmental regulations are a detrimental factor for firms' competitiveness, performance, and productivity.

In the context of the Sustainable Economic Development Plan proposed by the Italian government, emphasis has been put on environmental protection. Italy has made substantial progress in reducing air emissions: according to the ISPRA (*Istituto Superiore per la Protezione e la Ricerca Ambientale*)[1], the level of CO_2 emissions from manufacturing and construction sectors decreased up to 44% from 1990 to 2018. Even though the Italian economy has been under environmental regulatory pressure for a long time, only few studies have addressed the trade-offs between environmental policy and productivity. Among these studies, the vast majority were focused on national level. By contrast, no studies have been found at sector level. The aim of this work is to analyze the effect of environmental policies on productivity in thirteen Italian manufacturing industries. To address this issue, we use an approach proposed by Chung et al. (1997). In this paper the authors use a Joint Production Model (JPM) and Malmquist index to develop a new index, a Malmquist-Luenberger (ML) index that implies modelling the joint production of good (desirable) and bad (undesirable) outputs. The initial efforts to incorporate bad output in economic growth analysis were undertaken by

[1]Link: https://annuario.isprambiente.it/sys_ind/357

Ayres and Kneese (1969) and Leontief (1970). They incorporated bad output production and pollution abatement into a general equilibrium framework. More recently, Chung et al. (1997) proposed the ML index which incorporates an undesirable output into the Malmquist index, together with the assumption of the direction vector proposed by Luenberger in 1992. This index can be decomposed into two indices that explain technical change, shifts in the production frontier, and changes in technical efficiency, change in distance of an observation from the production frontier.

We operationalize the model by applying the Malmquist-Luenberger index to a panel data set of 13 manufacturing industries in Italy, using a three-output/three-input technology during the period from 1995 to 2017 respectively. The remainder of this paper is organized as follows. We provide a review of the literature on the effect of environmental regulations on the productivity growth in the manufacturing sector, in section 2. This section is followed by the description of the productivity index in Section 3. Section 4 discusses the data and the results. Section 5 provides some statistical results from bootstrapping and Section 6 concludes.

2. **Literature review**

The debate over environmental regulation has two principal concerns. First, there are concerns about whether the regulation optimal in the sense that marginal benefits equal marginal costs. Second, there are concerns about its impact on productivity and competitiveness. The conventional hypothesis holds imposing regulations results in higher production costs and declining competitiveness of nations or industries subject to those environmental regulations (Pasurka, 2008). The policy of invest in new technology for reducing the emissions are likely to add more pressure on a national or industrial productivity and competitiveness.

There have been numerous studies that investigated the relationship between environmental regulations and the productivity performance (e.g., Manello, 2017; Peng, 2020) as well as studies that investigated the relationship between environmental regulations and economic growth (e.g., Wang and Shao, 2019; Song et al., 2021; Sun et al., 2021). Most of these empirical studies examine the consequences using national data. Only a few studies have been made of the industry-level and most concentrate on the manufacturing sector.

Early studies reviewed by US Congressional Budget Office (1985) found that although statistically insignificant, pollution abatement costs were associated with reduced output. Conrad and Wastl (1995) investigated ten manufacturing industries in West Germany between 1975 and 1991 and found a decline in total factor productivity (TFP) caused by pollution abatement activities. Similarly, Dufour et al. (1998) investigated 19 manufacturing industries in Quebec and found declining total factor productivity. Gray and Shadbegian (2003) in their analysis on plant-level data found plants with higher pollution abatement activity have significantly lower productivity. Lanoie et al. (2008) investigated the effect of environmental regulations on the total factor productivity of the Quebec manufacturing sector. Using a sample of seventeen industries in the period 1985-1994, the authors found environmental regulations have a negative effect on TFP. In their investigation on eight manufacturing industries in Japan, the Netherlands, Germany, and the United States, Aiken et al. (2009) found there were negligible effects for Japanese and Dutch manufacturing industries, while annual productivity growth declined by 0.11 percent for the United States and increased by 0.24 percent for German manufacturing industry. Krautzberger and Wetzel (2012) calculated the Malmquist-Luenberger productivity index to investigate the consequences of environmental regulations on the productivity of the European commercial transport industry. According to their analysis the environmental regulations causes a decrease in productivity of the EU transport industry.

However, there are also studies using both county and industry level data that found a positive effect between environmental regulation and productivity. Authors like Meyer (1992) explored the relation between environmental regulation and the economic performance using an index of 20 environmental policy indicators. Meyer points out that countries with more stringent environmental regulations registered higher rates of economic performance. Later, Meyer (1996) in a second investigation discovered a positive (even statistically insignificant) relationship between environmental regulation and country economic performance. Chung et al. (1997) analyzed adjusted productivity growth and its decomposed indexes for Swedish paper and pulp mills between 1986 and 1990. From their empirical outcomes, it seems that productivity growth increases when undesirable outputs are taken into consideration. Hernandez-Sancho et al. (2000) investigate the relative efficiency of a sample of Spanish producers of wooden goods and furnishing under environmental regulations. The main result that authors carry out is the fact that the firms

are less likely to be affected by regulations where they enjoy some competitive advantages in terms of external economies. Berman and Bui (2001) used plant-level data for oil refineries in the United States and found that during 1982–1992, productivity for the heavily regulated refineries was five percentage points higher than the (declining) national average. Domazlicky and Weber (2001) applied a Malmquist-Luenberger (ML) index to manufacturing data from 48 states in the USA for a period from 1988 to 1994 and found state manufacturing adjusted productivity exhibited a of 1.40 percent annual growth rate. The authors point out that the measured productivity growth was significantly lower (0.6% versus 1.4% annual rate) when toxic releases were not included in the production set. Tsai (2002) investigated the period from 1987-1997 and calculated the total factor productivity for 15 manufacturing industries in Taiwan. She found environmental regulations overall had a positive effect on industry productivity for all 15 Taiwan manufacturing industries. Yörük and Zaim (2005) employed both the Malmquist (M) index, which includes only the good output, and ML index, which includes good and bad outputs, to analyse productivity growth and its decomposed sources for OECD countries during 1985–1998. The authors found that compared to the M index, the ML index shows average productivity growth that is 1.2 percent higher.

In a recent study, Lee, Wilson, Pasurka (2015) use a Joint Production Model (JPM) and employed the Malmquist-Luenberger productivity index to examine productivity growth. Using a sample of thirty-five airline companies they conclude the pollution abatement activities undertaken by airlines reduce productivity growth. Chen, et al. (2018) investigated 36 industrial sectors in China from 2000 to 2014. According to their study, industrial adjusted total factor productivity (TFP) declines by 0.02% per year on average. Hille and Möbius (2018) exploring a panel data of 14 manufacturing sectors across 28 OECD countries, found increases in environmental policy stringency have a positive effect on productivity growth.

Beltrán-Esteve, et al. (2019) assess the change in environmental productivity and its determinants for the European Union-28 (EU-28) between 2001 and 2016. The authors use an expression of environmental productivity, which is measured by a global additive Luenberger-meta-frontier framework, to define total factor productivity, which was computed by incorporating the undesirable output into the production set. According to the authors, the environmental productivity has improved, and the existing EU-15 members register higher growth rates relative to those members that joined the EU after the 2000s (EU-Others). Miao et al. (2019) assesses a positive effect of the market-motivated

environmental regulation on the atmospheric environment total factor productivity (AETFP). Recent empirical research that uses the difference-in-difference framework, has corroborated the significant inhibitory effect of the environmental regulation on total factor productivity (e.g., Tang et al., 2020; Chen et al., 2021), and on industrial economic growth (e. g., Liu et al., 2021).

To the best of our knowledge there has not been any studies on the productivity of Italian manufacturing industries that take into consideration environmental issues. While Beltrán-Esteve, et al. (2019) included Italy in their study, their investigation was conducted using data from EU-28 countries. The authors found an improvement on adjusted productivity (modelling good and bad outputs) for Italy during the period of 2001-2016. Similarly, Italy was included in the Sickles and Jeon (2004) study as part of their OECD sample. Using an ML productivity index, the authors found an increase in adjusted productivity for Italy for the period 1980-1990.

3. Productivity Indices

Malmquist-Luenberger productivity index is an index that is based on the directional distance function and uses a direction vector that treats the output (or input) asymmetrically. Our model is an output-oriented model, and we choose the direction to be $g = (y^t, -b^t)$, which credits a producer for producing more good outputs and less bad outputs. The choice of this directional is related to the fact that there might be institutional regulations limiting an increase in bad outputs, specifically pollutant emissions. Chung et al. (1997) introduces the ML index arguing that it explicitly credits firms or industries for increasing good outputs and reducing undesirable outputs. The index is computed using a data envelopment analysis approach.

To explain the output-based productivity index, we are reporting the standard framework proposed by Chung et al., (1994). The first assumption is related to the production set. The production set P^t for each time period t = 1,…….,T transforms the inputs $x^t \in R_+^N$ into outputs, goods $y^t \in R_+^M$ and bads $b^t \in R_+^I$:

$$P^t(x) = \{(y, b): x\ can\ produce\ (y, b)\}, x \in R_+^N \quad (1)$$

In the general framework, the production set is composed of the set of all feasible input and output vectors. So, for each input vector x^t, the output set P^t is composed of the total amount of good and bad outputs (y^t, b^t) produced by the input vector. To assess the problem related to the fact that the reduction of bad outputs is costly, in the general framework is imposed weak disposability of outputs, i.e.

$$(y^t, b^t) \in P^t(x) \text{ and } 0 \leq \theta \leq 1 \text{ imply } (\theta y^t, \theta b^t) \in P^t(x) \quad (2)$$

This condition states a reduction of undesirable outputs can be achieved by a simultaneous reduction in the goods, given fixed input levels. So, if x^t can produce output (y^t, b^t), then it is feasible to reduce these outputs proportionally by θ. This axiom can be contrasted with the strong disposability condition:

$$(y^t, b^t) \in P^t(x) \text{ and } (y'^t, b'^t) \leq (y^t, b^t) \text{ imply } \left(y'^t, b'^t \in P^t(x)\right) \quad (3)$$

Imposing this condition allows for the non-proportional reduction in both good and undesirable outputs. Generally, we can costlessly dispose of the outputs. While this is acceptable for the good output, it does not for the undesirable output when there are environmental policies. The assumption that the good outputs are freely disposable is constructed as follow,

$$(y^t, b^t) \in P^t(x) \text{ and } y'^t \leq y^t \text{ imply } \left(y'^t, b^t \in P^t(x)\right) \quad (4)$$

Together, equation (2) and equation (4) model the jointly weakly disposable between the good (freely disposable) and bad (not freely disposable) outputs. The authors also model the property that desirable and undesirable outputs are jointly produced introducing “null-joint.” property. In other words, you cannot produce one without the other, i.e.,

$$\text{if } (\theta y^t, \theta b^t) \in P^t(x) \text{ and } b^t = 0 \text{ then } y^t = 0 \quad (5)$$

To develop the ML productivity index, the directional distance function is defined as:

$$\vec{D}_0^t(x^t, y^t, b^t; g) = sup\{\beta | (y^t + \beta g_y, b^t - \beta g_b) \in P^t\ (x^t)\} \quad (6)$$

where β is the maximum feasible expansion of the good output and contraction of the bad outputs. The maximum expansion and contraction of outputs are identically proportions for the specified level of inputs. g_y and g_b are subvectors for y^t and b^t of the direction g .[2] Chung et al. (1997) output-oriented Malmquist–Luenberger productivity index between periods t and $t+1$ is defined as:

$$ML_0^{t,t+1} = \left(\frac{\{1+\vec{D}_0^t(x^t,y^t,b^t;y^t,-b^t)\}}{\{1+\vec{D}_0^t(x^{t+1},y^{t+1},b^{t+1};y^{t+1},-b^{t+1})\}} * \frac{\{1+\vec{D}_0^{t+1}(x^t,y^t,b^t;y^t,-b^t)\}}{\{1+\vec{D}_0^{t+1}(x^{t+1},y^{t+1},b^{t+1};y^{t+1},-b^{t+1})\}} \right)^{1/2} \quad (7)$$

The Malmquist–Luenberger index can be decomposed as:

$$ML_0^{t,t+1} = MLECH_t^{t+1} * MLTCH_t^{t+1} \quad (8)$$

where $MLECH_t^{t+1}$ and $MLTCH_t^{t+1}$ denote efficiency changes and technological changes respectively. We can write efficiency change and technical change as:

$$MLECH_0^{t,t+1} = \frac{\{1+\vec{D}_0^t(x^t,y^t,b^t;y^t,-b^t)\}}{\{1+\vec{D}_0^{t+1}(x^{t+1},y^{t+1},b^{t+1};y^{t+1},-b^{t+1})\}} \quad (9)$$

and

$$MLTCH_0^{t,t+1} = \left[\frac{\{1+D_0^{t+1}(x^{t+1},y^{t+1},b^{t+1};y^{t+1},-b^{t+1})\}}{\{1+D_0^t(x^{t+1},y^{t+1},b^{t+1};y^{t+1},-b^{t+1})\}} * \frac{\{1+D_0^{t+1}(x^t,y^t,b^t;y^t,-b^t)\}}{\{1+D_0^t(x^t,y^t,b^t;y^t,-b^t)\}} \right]^{1/2} \quad (10)$$

[2] Briec (1995) specifies a distance function for the growth of the technology like Luenberger's shortage function. See Luenberger (1992a, 1992b, 1994a, 1994b, 1995a, 1995b).

The $ML_0^{t,t+1}$ productivity index indicates no change in productivity if it equals unity, $ML_0^{t,t+1} = 1$, an improvement in productivity if it is greater than one, $ML_0^{t,t+1} > 1$ and a decrease in productivity if is less than unity, $ML_0^{t,t+1} < 1$. Technical change in the production of the desirable output and undesirable output is measured by the $MLTCH_t^{t+1}$ index, which is the geometric mean of the shift in the production possibilities frontier. In other words, technical progress measures the shifts of the production possibilities frontier in the direction of "more goods and fewer bads", $MLTCH_t^{t+1} > 1$. If the $MLTCH_t^{t+1}$ index equals unity, this indicates there is no shift in the production possibilities frontier. If the $MLTCH_t^{t+1}$ index is less than unity, this indicates an inward shifting of the production frontier in the direction of fewer goods and more bads. Finally, $MLECH_t^{t+1}$ measures the ratio of "how close" an observation is to its respective frontiers. If efficiency changes exceed unity (less than unity), it indicates that the observation is in the same distance from the production frontier in period *t+1* than it was in period t. An efficiency index, MLECH, equal to unity indicates that the observation is in the same distance from the production frontier in period $t+1$ as it was in t.

The calculation of the Malmquist–Luenberger index is achieved by solving a set of nonparametric linear programming problems. The distance function of observation k' at time t is constructed using the time t frontier as:

$$\vec{D}_0^t\left(\mathrm{x}^{\mathrm{t}}(\mathrm{k}'), \mathrm{y}^{\mathrm{t}}(\mathrm{k}'), \mathrm{b}^{\mathrm{t}}(\mathrm{k}'); \mathrm{y}^{\mathrm{t}}(\mathrm{k}'), -\mathrm{b}^{\mathrm{t}}(\mathrm{k}')\right) = \mathrm{Max}\ \beta(\mathrm{k}') \tag{11}$$

$$\mathrm{s.t} \quad \sum_{\mathrm{k}=1}^{\mathrm{K}} \mathrm{z}^{\mathrm{t}}(\mathrm{k}) \mathrm{y}_{\mathrm{m}}^{\mathrm{t}}(\mathrm{k}) \geq (1+\beta) \mathrm{y}_{\mathrm{m}}^{\mathrm{t}}(\mathrm{k}) \qquad \mathrm{m} = 1, \ldots, \mathrm{M}$$

$$\sum_{\mathrm{k}=1}^{\mathrm{K}} \mathrm{z}^{\mathrm{t}}(\mathrm{k}) \mathrm{b}_{\mathrm{i}}^{\mathrm{t}}(\mathrm{k}) = (1-\beta) \mathrm{b}_{\mathrm{i}}^{\mathrm{t}}(\mathrm{k}) \qquad \mathrm{i} = 1, \ldots, \mathrm{I}$$

$$\sum_{\mathrm{k}=1}^{\mathrm{K}} \mathrm{z}^{\mathrm{t}}(\mathrm{k}) \mathrm{x}_{\mathrm{n}}^{\mathrm{t}}(\mathrm{k}) \leq \mathrm{x}_{\mathrm{n}}^{\mathrm{t}}(\mathrm{k}) \qquad \mathrm{n} = 1, \ldots, \mathrm{N}$$

$$\sum_{\mathrm{k}=1}^{\mathrm{K}} \mathrm{z}^{\mathrm{t}}(\mathrm{k}) \geq 0 \qquad \mathrm{k} = 1, \ldots, \mathrm{K}$$

The $z^t(k)$ are the weights assigned to each observation k when constructing a production possibilities frontier. The condition of positivity constraints on the intensity variable, $z^t(k)$, allows us to construct the model that exhibits constant returns to scale[3]. The inequality constraints on the good outputs, m = 1,...., M, indicate they are freely disposable. Together with the equality constraints on the bad outputs (i = 1,...,I), the bad outputs are not freely disposable.

The calculation of ML productivity index requires solving four distance functions, $\vec{D}_0^{t,t}$, $\vec{D}_0^{t,t+1}$, $\vec{D}_0^{t+1,t}$, $\vec{D}_0^{t+1,t+1}$, which measure distance of an observation to the frontier (see Appendix A). The distance functions for the mixed- period LP problems, $\vec{D}_0^{t,t+1}$, $\vec{D}_0^{t+1,t}$, can yield infeasible solutions if the observations are outside the production set (see Appendix B). For example, the production possibilities frontier constructed by the observations *t* may not contain on observation from period *t+1.* This would happen for those observations (country or producer) that are very innovative and their data at time *t+1* are located outside the current (period t) frontier. To avoid infeasible LP problems, we introduce a modification of the standard definition of the bad not being freely disposable, which is modeled in the production function via a strict equality constraint for the undesirable outputs. Following Färe et al. (2014) and Färe et al. (2016), we impose a modified weak disposability assumption, which is modeled by changing the strict equality constraint to a less than or equal constraint on the undesirable outputs. This assumption was firstly introduced by the authors for eliminating the possibility of a downward sloping of the frontier. Modifying the equality to an inequality yields unbounded output sets and treats the undesirable output as not freely disposable. This will not lead to incorrect biases results because weak disposability holds even under strong or free disposability. The assumption has been proved by Färe et al. in their book published in 1994. Also, Cheng (2014) proved that using strong disposability of undesirable outputs will not bias the results and he recommended that strong disposability of bads should be applied when we use direction distance function (DDF) approach. According to Cheng (2014), using the disposability assumption will not lead to infeasible LP and will not bias results because the evaluated DMU will never be projected into the infinitely upward

[3] Färe and Grosskopf (1996), argue that constant returns to scale is a necessary condition form the resulting productivity indexes to be true total factor productivity index.

extension of the Production Possibility Set if we treat good and bad outputs asymmetrically (see Appendix C). This relaxing assumption, i.e., changing the equality restriction on undesirable outputs to in-equalities in the production technology, has also been used by Du et al. (2018). So, the linear programming model to be solved for observation k' at t will take the form:

$$\vec{D}_0^t\left(\mathrm{x^t(k')}, \mathrm{y^t(k')}, \mathrm{b^t(k')}; \mathrm{y^t(k')}, -\mathrm{b^t(k')}\right) = \mathrm{Max}\ \beta(\mathrm{k'}) \tag{12}$$

$$\mathrm{s.t} \quad \sum_{\mathrm{k=1}}^{\mathrm{K}} \mathrm{z^t(k) y_m^t(k)} \geq (1+\beta)\mathrm{y_m^t(k)} \qquad \mathrm{m} = 1, \ldots, \mathrm{M}$$

$$\sum_{\mathrm{k=1}}^{\mathrm{K}} \mathrm{z^t(k) b_i^t(k)} \leq (1-\beta)\mathrm{b_i^t(k)} \qquad \mathrm{i} = 1, \ldots, \mathrm{I}$$

$$\sum_{\mathrm{k=1}}^{\mathrm{K}} \mathrm{z^t(k) x_n^t(k)} \leq \mathrm{x_n^t(k)} \qquad \mathrm{n} = 1, \ldots, \mathrm{N}$$

$$\sum_{\mathrm{k=1}}^{\mathrm{K}} \mathrm{z^t(k)} \geq 0 \qquad \mathrm{k} = 1, \ldots, \mathrm{K}$$

Where the mixed- period LP problem resembles Equation (12) except for the time superscripts on the right-hand side of the constraints that differs from the time superscripts on the left-hand side of the constraints. In other words, for output set from period t and observation from period t+1, the observation under valuation appears on the right-hand side of the constraints and the output set that is determined by all the observations from period t appears on the left-hand side of the constraints.

For comparison purposes, we also calculate the standard Malmquist (M) index, which is the one of the traditional indices we find in the literature for calculating the productivity growth without considering the undesirable output. For more further details on how the M index linear programming model is constructed see Chung et al. (1997).

4. Data and Results

Operationalizing the model requires information on input quantities as well as good and bad output quantities. Specifically, we need data on the capital stock, number of employees, intermediate inputs, GDP, and air emissions for Italian manufacturing industries. We obtain the information needed from the OECD website, OECD STructural ANalysis (STAN) Dataset for Industrial Analysis [4]. The technology modeled in this study consists of one good output, Gross output, and two undesirable outputs – carbon dioxide (CO_2) and non-methane volatile organic compounds (NMVOC). We choose these two substances because of their contribution to climate change and health problems for humanity. The inputs consist of total hours worked by all employees for each manufacturing industry, net capital stock, and intermediate inputs. The intermediate inputs include all the inputs (others from capital and labur) that are consumed during the production process. These inputs include energy, materials, and service (including any rentals for machinery and equipment) (OECD, 2001).

Our sample consists of a balanced panel of 13 manufacturing industries for the period from 1995 to 2017[5]. Table 1 presents summary statistics for our sample, while Appendix D provides information about the desirable output, undesirable outputs, and inputs.

Table 1 here

To model the production technology set we use a contemporaneous frontier. In this setting, the production technology for period *t* is constructed using observations from period *t,* while the production technology of period *t+1* consists of observations from period *t+1*. Assuming the production technology sets are homogeneous across industries, each observation for a given year is compared to a production frontier, which is constructed from a combination of all the industries present in our sample.

[4] Link: https://stats.oecd.org/Index.aspx?DataSetCode=STANi4

[5] We use data downloaded from OECD STAN dataset in January 2020 and September 2020. The current version of STAN is based on the International Standard Industrial Classification of all economic activities, Revision 4 (ISIC Rev. 4). Earlier versions of STAN were based on ISIC Rev. 3 and, prior to 2000, ISIC Rev. 2 (the latter covering the manufacturing sector only).

The model generates results for each two-year pair in our sample. For every 2-year pair, four LP problems are solved for both technologies – one with the regulated undesirable output (ML index) and one without the undesirable output (M index).

Table 2 presents the geometric means of ML and standard M indexes for the period from 1995 to 2017 for the manufacturing sector and its associated industries. Looking at the results for the ML index on an industry-by-industry basis, we observe substantial variation between industries, ranging from a low of 2.42 per cent annual productivity decline for Textiles, Wearing apparel, Leather products industry (C13-C15), to a high of a 1.8 per cent annual growth rate for Transport equipment industry (C29-C30).

Table 2 here

On average, for the ML index, productivity increases by 0.06 percent per year, due mainly from increases in efficiency changes (MLECH), of 0.04 percent per year. The technical changes (MLTCH) shows an improvement of 0.03 percent per year. On the other hand, for the Malmquist index, average productivity declines by 0.45 percent per year, with technical change declining by 0.52 percent per year and the efficiency showing an improvement of 0.07 percent per year for all industries.

If we look at the results for the ML index for those industries with productivity growth, it is evident the growth by technical progress. So, those industries are moving in a direction of higher desirable output and lower undesirable output. The two exceptions are Rubber and plastics products, and other non-metallic mineral products industry (C22-C23) and Basic metals and fabricated metal products except machinery and equipment industry (C24-C25). These industries show increases in productivity thanks to improvements in MLECH, which offsets a declining MLTCH. The industries that show a loss of productivity are also accompanied by a decline in the MLTCH, so when the frontier shifts inward, it moves in the direction of “fewer goods and more bads”. Most of these industries show constant MLECH, except the Wood and paper products; printing and reproduction industry (C16-C18) which shows an improvement in MLECH.

The results suggest that for the ML index, most industries are posting higher productivity growth or smaller productivity declines relative to the Malmquist index, except for the Wood and paper products; printing and reproduction industry (C16-C18). The

relatively higher productivity growth or smaller productivity decline is attributed to the ML model which incorporates the undesirable output and credits industries for reducing production of the bad output. According to Färe et al. (2001) for a given input vector, if the percent increases in desirable output exceeds (is less than) the absolute value of the percentages decreases in the undesirable output, the growth rate of the traditional productivity (M index) exceeds (is lower than) the growth rate of the adjusted productivity (ML index). Like the M productivity index, MLTCH show a higher productivity growth or smaller productivity decline relative to the Malmquist technical changes (MTCH) index. In contrast, most industries are posting a lower (equal) MLECH index relative to Malmquist efficiency changes (MECH) index, except Electrical equipment industry (C27) and Transport equipment industry (C29-C30). The only industry with virtually the same values for the ML and M indexes, the MLTCH and MTCH indexes and of MLECH and MECH indexes, is "Basic metals and fabricated metal products except machinery and equipment" industry (C24-C25). Both productivity (ML) and its decomposition (MLTCH and MLECH) are not affected by environmental regulations in this industry.

If we look at efficiency changes industry-by-industry, for both ML and M index, we find industries with no efficiency changes (MLECH=1 and MECH=1) and industries with both increasing and decreasing efficiency changes. The only industry that shows a declining MLECH index is the Electrical Equipment industry (C27), with a decline of 0.1 percent per year. For the MECH index, two industries show declining levels of technical efficiency - Electrical Equipment industry (C27) and Transport equipment industry (C29-C30).

We find only four manufacturing industries that exhibit improved efficiency (MLECH >1) for the ML index, which means that those industries are closer to the frontier in period *t+1* than they were in the period *t*. On the other hand, the M index shows a slight improvement of MECH for seven industries. The difference in having more industries with improvements in efficiency changes under the M index relative to the ML index might suggest environmental policies cause the loss of efficiency for those industries with a low MLECH relative to MECH. Food products, beverages, and tobacco industry (C10-C12), under M index shows the highest efficiency changes, 0.5 per cent per year, while for the ML index, Chemicals and chemical products industry (C20) shows the highest MLECH, i.e., 0.17 percent.

In contrast, technical change under ML (MLTCH) shows different trends. If we compare the results industry-by-industry, seven industries exhibit increases in MLTCH, while

the other six industries show declining MLTCH. The production possibility frontier of industries with declining MLTCH has shifted inward (i.e., technical regress), in the direction of "fewer goods and more bads", which suggests most of these industries have yet to adopt new technology which increases the desirable output and decreases the undesirable output. Technical changes for the M index (MTCH) shows improvements only for Basic pharmaceutical products and pharmaceutical preparations industry (C21) and Transport equipment industry (C29-C30), respectively 0.28 and 0.15 per cent per year. The other industries, under M index, show a decline in MTCH.

Table 3 presents the geometric mean of productivity change, technical change, and efficiency change for each two-year period analyzed in this investigation . Both the average ML and M indexes show declining productivity when the world economy was been hit by the global economic crises. For the ML index, the annual changes in productivity growth range from a low of -4.76 per cent in 2008-2009 to a high of 4.60 per cent in 2009-2010. Under Malmquist index, the annual change in productivity growth ranges from an increase of 2.70 per cent in 2009-2010 to a 5.41 per cent decrease in 2008-2009. Given the results for individual industries, it is not surprising that when we compare the average annual changes in each period for the entire manufacturing sector, the ML index shows higher productivity growth or a smaller productivity decline than the M index. Only in 2007-2008 and 2014-2015 we find the reverse, when M index shows a higher productivity increase or a smaller productivity decline.

Table 3 here

Changes in efficiency for the ML index range from an increase of 0.40 per cent for both 1998-1999 and 2015-2016, to a 0.52 per cent decline for 2008-2009, while technical change ranges from -4.31 in 2008-2009 to 4.27 percent in 2009-2010. The change in efficiency, for the M index, ranges from 0.81 per cent in 2015-2016 to -0.96 per cent for 2010-2011, while technical change posted growth from 2.57 per cent in 2009-2010 to -4.66 per cent in 2008-2009.

Based upon the above results, the conclusions that we can draw are that during the last 23 years, firms in the manufacturing sector made great strides in reducing air emissions. When reducing air emissions, some industries adopted investment in environmental technology strategy (i.e., technical progress), while others adopted best-practise management measures (i.e., improved efficiency). This is evident when we compare MLTCH

with MLECH. The proposals to invest in new technology for reducing air emissions seem to put less pressure on Italian manufacturing industries.

5. Bootstrapping

To provide robustness of the results, we use the bootstrapping approach introduced by Simar and Wilson (1998, 1999, 2000a, b). Simar and Wilson (1999) developed a bootstrap method to estimate the sampling distribution and confidence intervals for the Malmquist index. They introduced a method for correcting the bias of the Malmquist index that accounts for the intertemporal dependencies between the distance functions, thus creating bootstrap samples simultaneously for two periods. Subsequently, the methodology was extended to the analysis of the Malmquist-Luenberger index by Jeon and Sickles (2004). The main problems pointed out in computing the indexes were first, the use of nonparametric programming estimators, which are considered to be deterministic, and second to the measure of the performance based on a true and unobservable production frontier. According to the authors, the estimates of the frontier are based on finite samples, which result in efficiency and productivity measures being subject to the sampling variation of the frontier (Jeon and Sickles, 2004). This methodology was recently used by Lee, et al. (2015) in testing the reliability of the ML index for thirty-five airline companies.

Following Lee, Wilson and Pasurka (2015), we adopt` the bootstrapping approach of Hampf (2013) to test the reliability of our result. To determinate whether changes in productivity growth, efficiency or technical change are statistically significant, we use a 95 per cent confidence interval generated from bootstrapping. We use the original estimators to construct the confidence intervals of the true index. The model replicates the dataset to generate an appropriately large number of pseudo samples (B=2000) and estimates the uncorrected results, the bias-corrected results, and confidence intervals. The indexes are statistically different from unity if the confidence interval does not contain the value of one. The results of bias-corrected estimates for the ML index are presented in Table 4. The results show that there is significant aggregate productivity change for most industries. The confidence intervals derived from the bootstrap show that two industries, i.e., food production, beverage, and tobacco (C10-C12) and textiles, wearing, leather and related production (C13-C15), have significant productivity changes for each two-year pair. Evaluating

the disaggregated indexes, MLTCH and MLECH, we cannot conclude if efficiency change or technological change are driving productivity change. For technological change, only food production, beverage, and tobacco (C10-C12) industry does not show significant changes. Instead, the rest of industries show significant changes, mainly for the period of 2006-2011. In addition, for efficiency change, only Chemicals and chemical products shows significative changes during the period of study. The result of bias-corrected MLTCH and MLECH indexes are provided in Appendix E and Appendix F.

Table 4 here

6. Conclusions

This study focuses on measuring adjusted productivity growth in Italian manufacturing industries when both desirable and undesirable output are taken into consideration. Using a dataset of thirteen manufacturing industries between 1995 and 2017, a ML productivity index was employed to measure the TFP index and its decomposition indexes (efficiency and technical change index). The average annual increase in ML productivity growth is 0.06 percent per year, which is primarily attributed to efficiency changes. When the undesirable outputs are not included in the production technology, productivity growth (M productivity growth) declines by 0.45 percent per year. An important result stemming from our analysis is that when air emissions are targeted by the Italian government, such policy action lowers adjusted productivity growth for only one industry, i.e., Wood and paper production; printing and reproduction of recorded media (C16-C18), while adjusted productivity is less affected in all other industries.

One important limitation of this study is the small sample size, which is due to data availability. To overcome this problem, we tested the reliability of our results using a bootstrap approach. Moreover, the drawback of using a dataset with a relatively low ratio of observations to constraints is that many observations fall on the production frontier. Hence, these observations are identified as technically efficient. When decomposing changes in productivity into (1) technical change and (2) changes in technical efficiency, we find that changes in productivity are closely linked to technical change. A larger sample size could provide a more accurate picture of productivity growth at industry level. Another limitation of the work is that the model does not explicitly account for productivity differences across industries (i.e., the composition effect), whereas several scholars stress that growth is

brought about by changes in sectorial composition (Kuznets, 1971; Rostow, 1971; Chenery and Syrquin, 1975; Baumol et al. 1989). This is another issue that future studies should address in detail.

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Tables

Table 1. Descriptive statistic (Millions)

Year	Variable	Units	Mean	Std. Dev.	Minimum	Maximum
1995	Gross output	Euro	65789.15	35528.54	12522.5	119755.4
	Carbon Dioxide (CO_2)	Tonnes	1.39e+07	240008	4.18e+07	1.39e+07
	NMVOC	Tonnes	22392.7	4735	82038	22392.7
	Hours worked-employees	Hours	3.657.413	430.442	1.313.856	3.657.413
	Net Capital Stock	Euro	14268.94	6.613.189	48723.97	14268.94
	Intermediate input	Euro	27161.04	7.565.221	94309.69	27161.04
2017	Gross output	Euro	73595.38	41331.01	21873.77	142963.2
	Carbon Dioxide (CO_2)	Tonnes	6653660	8041646	228084	2.49e+07
	NMVOC	Tonnes	17795	12588.41	1721	43963
	Hours worked-employees	Hours	4.480.506	2.964.953	268.961	9.894.484
	Net Capital Stock	Euro	37370.48	17102.3	16205.69	67613.14
	Intermediate input	Euro	54077.92	31314.34	13848.35	111892.6

Note: Data provided from OECD STAN dataset in January 2020 and September 2020

Table 2. Decomposition of Average Annual Changes, 1995-2017

		Malmquist-Luenberger			Malmquist		
	ISIC (Rev.4)	ML	MLTCH	MLECH	M	MTCH	MECH
Food products, beverages and tobacco	C10-C12	1.0001	1.0001	1.0000	0.9939	0.9891	1.0049
Textiles, wearing apparel, leather and related products	C13-C15	0.9758	0.9758	1.0000	0.9734	0.9734	1.0000
Wood and paper products; printing and reproduction of recorded media	C16-C18	0.9990	0.9976	1.0014	0.9992	0.9977	1.0015
Coke and refined petroleum products	C19	0.9940	0.9940	1.0000	0.9832	0.9832	1.0000
Chemicals and chemical products,	C20	1.0053	1.0036	1,0017	0.9997	0.9980	1.0017
Basic pharmaceutical products and pharmaceutical preparations	C21	1.0110	1,0110	1.0000	1.0028	1.0028	1.0000
Rubber and plastics products, and other non-metallic mineral products	C22-C23	1,0003	0.9988	1.0015	0.9999	0.9984	1.0015
Basic metals and fabricated metal products, except machinery and equipment	C24-C25	1.0013	0.9997	1.0016	1.0013	0.9997	1.0017
Computer, electronic and optical products,	C26	1.0034	1.0034	1.0000	0.9977	0.9971	1.0006
Electrical equipment,	C27	1.0005	1.0016	0.9990	0.9949	0.9976	0.9974
Machinery and equipment n.e.c.,	C28	1.0029	1.0029	1.0000	0.9994	0.9975	1.0018
Transport equipment	C29-C30	1.0180	1.0180	1.0000	0.9990	1.0015	0.9975
Other manufacturing; repair and installation of machinery and equipment,	C31-C33	0.9968	0.9968	1.0000	0.9964	0.9964	1.0000
Manufacturing	C10-C33	**1.0006**	**1.0003**	**1.0004**	**0.9955**	**0.9948**	**1.0007**

Table 3. Average Annual Changes in each period of the indices

	Malmquist_Luenberger			Malmquist		
	ML	MLTCH	MLECH	M	MTCH	MECH
1995-1996	0.9981	0.9950	1.0034	0.9946	0.9913	1.0033
1996-1997	0.9963	0.9977	0.9985	0.9984	0.9991	0.9993
1997-1998	1.0009	1.0002	1.0007	0.9891	0.9857	1.0035
1998-1999	0.9975	0.9939	1.0040	0.9926	0.9867	1.0060
1999-2000	1.0035	1.0035	0.9999	1.0003	0.9958	1.0045
2000-2001	0.9958	0.9979	0.9977	0.9910	0.9960	0.9950
2001-2002	0.9938	0.9914	1.0027	0.9925	0.9915	1.0011
2002-2003	0.9964	0.9974	0.9989	0.9905	0.9902	1.0003
2003-2004	1.0042	1.0020	1.0023	0.9980	0.9940	1.0041
2004-2005	1.0033	1.0043	0.9989	0.9974	0.9975	1.0000
2005-2006	1.0117	1.0099	1.0019	1.0016	0.9997	1.0018
2006-2007	1.0174	1.0180	0.9993	1.0050	1.0052	0.9998
2007-2008	0.9624	0.9624	1.0000	0.9836	0.9875	0.9961
2008-2009	0.9524	0.9569	0.9948	0.9459	0.9534	0.9921
2009-2010	1.0460	1.0427	1.0034	1.0270	1.0257	1.0013
2010-2011	1.0242	1.0279	0.9961	0.9951	1.0047	0.9904
2011-2012	0.9931	0.9929	1.0002	0.9890	0.9852	1.0038
2012-2013	0.9977	0.9983	0.9994	0.9958	0.9969	0.9988
2013-2014	1.0106	1.0081	1.0028	1.0053	1.0034	1.0018
2014-2015	0.9962	0.9977	0.9984	1.0080	1.0090	0.9991
2015-2016	1.0075	1.0037	1.0040	0.9951	0.9871	1.0081
2016-2017	1.0077	1.0059	1.0019	1.0056	1.0010	1.0045

Table 4. Bias-corrected Estimates of ML index

	Food products, beverages and tobacco,	Textiles, wearing apparel, leather and related products	Wood and paper products ; printing	Coke and refined petroleum products	Chemicals and chemical products	Basic pharmaceutical products	Rubber and plastics products , and othe	Basic metals and fabricated metal products	Computer , electronic and optical products	Electrical equipment	Machinery and equipment n.e.c.,	Transport equipment	Other manufacturing ; repair and installation of machinery
1995-96	0.9952*	0.9699*	1.0068*	0.9517*	1.0276*	1.0054	1.0019	1.0001	1.0207*	0.9965	1.0086*	0.9987	0.9952
1996-97	1.0124*	0.9918*	0.9925*	1.0226*	1.0003	1.0026	1.0077	0.9983	0.9702*	0.9723*	0.9935	1.0087	0.9805*
1997-98	0.9897*	0.9856*	1.0047	0.9584*	0.9993	0.9985	1.0056	0.9920*	1.0455*	1.0227*	1.0117*	1.0043	0.9896*
1998-99	0.9835*	0.9557*	1.0009	0.9833*	1.0202*	1.0083*	1.0083*	1.0000	0.9983	1.0050	1.0092	1.0063	0.9894*
1999-00	1.0557*	1.0207*	0.9958	0.9674*	0.9862*	1.0056*	1.0073*	1.0014*	0.9794*	0.9798	1.0292*	1.0180*	1.0016
2000-01	0.9788*	0.9831*	1.0082*	0.9675*	0.9902*	1.0022	0.9988	0.9975*	1.0288*	0.9967	1.0088	1.0004	0.9854*
2001-02	0.9890*	0.9484*	0.9926*	0.9767*	1.0203*	1.0005	1.0096*	0.9984	0.9841*	1.0112*	0.9838*	1.0086	0.9979
2002-03	1.0242*	0.9511*	0.9887*	0.9953*	1.0073*	1.0103*	0.9860*	1.0020*	0.9874*	1.0037	1.0203*	0.9908*	0.9838*
2003-04	0.9736*	0.9611*	1.0038*	0.9956*	1.0063*	1.0040	1.0034*	1.0043*	1.0234*	1.0199*	1.0286*	1.0219*	1.0060*
2004-05	1.0267*	0.9672*	0.9935*	1.0110*	0.9965	0.9996	1.0016	1.0161*	1.0142*	1.0012	1.0120*	1.0025	1.0014
2005-06	0.9833*	0.9828*	1.0035*	0.9794*	1.0094*	1.0265*	0.9972	1.0162*	1.0313*	1.0147	1.0337*	1.0660*	1.0075*
2006-07	1.0170*	1.0342*	1.0000	1.0133*	1.0119*	1.0174*	0.9963*	1.0050	1.0221*	1.0147*	1.0329*	1.0548*	1.0025*
2007-08	0.9782*	0.9085*	0.9896*	0.9931*	1.0254*	1.0296*	0.9847*	0.9940	0.8698*	0.8933*	0.8971*	0.9894*	0.9857*
2008-09	0.9823*	0.8994*	0.9836*	0.8987*	0.8940*	0.9812*	0.9721*	0.9470*	1.0398*	0.9893	0.8742*	0.9570*	0.9837*
2009-10	1.0239*	1.0635*	1.0131*	1.0473*	1.0839*	1.0612*	1.0192*	1.0259*	1.0392*	1.0836*	1.0632*	1.0717*	1.0010
2010-11	0.9867*	1.0264*	1.0096*	0.9864*	1.0098*	1.0652*	0.9960*	1.0006	1.0916*	1.0161*	1.0733*	1.0483*	1.0107
2011-12	0.9878*	0.9486*	0.9975*	0.9949*	0.9942*	1.0133*	0.9935	1.0115*	1.0077	0.9735*	1.0184*	0.9863	0.9846*
2012-13	1.0081*	0.9644*	0.9962*	1.0569*	1.0045*	1.0138*	0.9960*	1.0027	0.9451*	1.0014	0.9664*	1.0115*	1.0079*
2013-14	1.0073*	0.9939*	1.0047*	0.9868*	1.0051	0.9866*	1.0063*	1.0132*	1.0226*	1.0183*	1.0349*	1.0541*	1.0048
2014-15	1.0071*	0.9657*	0.9916*	1.0280*	1.0194*	1.0056	0.9976*	0.9998	0.9725*	1.0036	0.9481*	1.0125*	1.0027
2015-16	0.9947*	0.9731*	1.0082*	1.0146*	0.9976	1.0006	1.0062*	1.0114*	0.9968*	1.0155*	1.0072*	1.0572*	1.0152*
2016-17	0.9990	0.9862*	0.9950*	1.0382*	1.0230*	1.0071*	1.0064*	1.0001	1.0008	0.9984	1.0214*	1.0344*	0.9949*

Note: (*) denote significant difference from unit at 0.05

Appendices

(Not Intended for Publication)

Appendix A

If we suppose a production set at time *t*, $P^t(x^t)$, bounded by 0ACDE and production set at time *t+1*, $Pt^{+1}(x^{t+1})$ bounded by 0FGHJ and the observation $(y^{t,k}, b^{t,k})$, which is represented by point *K*, and belongs to $P^t(x^t)$ and $(y^{t+1,k}, b^{t+1,k})$, which is represented by point L and belongs to $P^{t+1}(x^{t+1})$ but not to $P^t(x^t)$, the four-distance function to be solved are the following:

- $\overrightarrow{D_0^t}(x^t, y^t, b^t; y, -b) \rightarrow$ distance of K from 0ACDE
- $\vec{D}_0^t(x^{t+1}, y^{t+1}, b^{t+1}; y, -b) \rightarrow$ distance of L from 0ACDE
- $\vec{D}_0^{t+1}(x^t, y^t, b^t; y, -b) \rightarrow$ distance of K from 0FGHJ
- $\vec{D}_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y, -b) \rightarrow$ distance of L from 0FGHJ

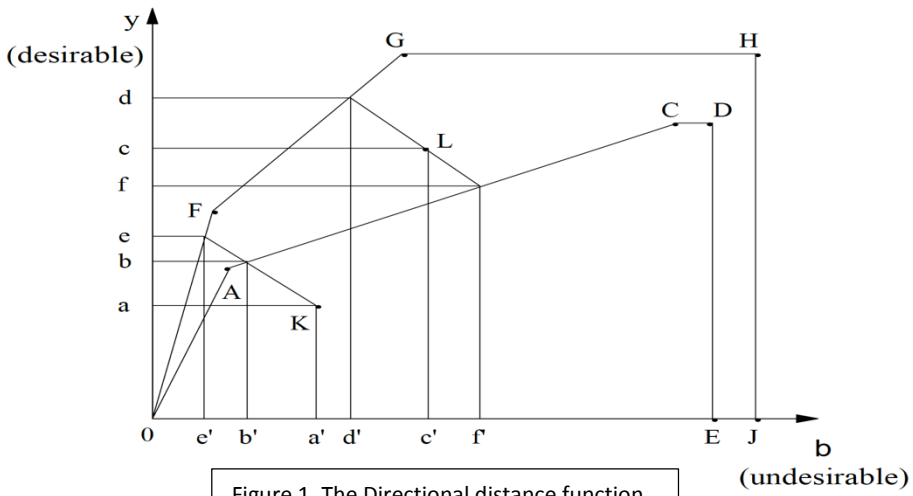


Figure 1. The Directional distance function

Appendix B

Figure 2 illustrates the potential problem of infeasible solution, when no simultaneous proportional expansion of the desirable output and contraction of the undesirable output on production set 0ABCDE is possible.

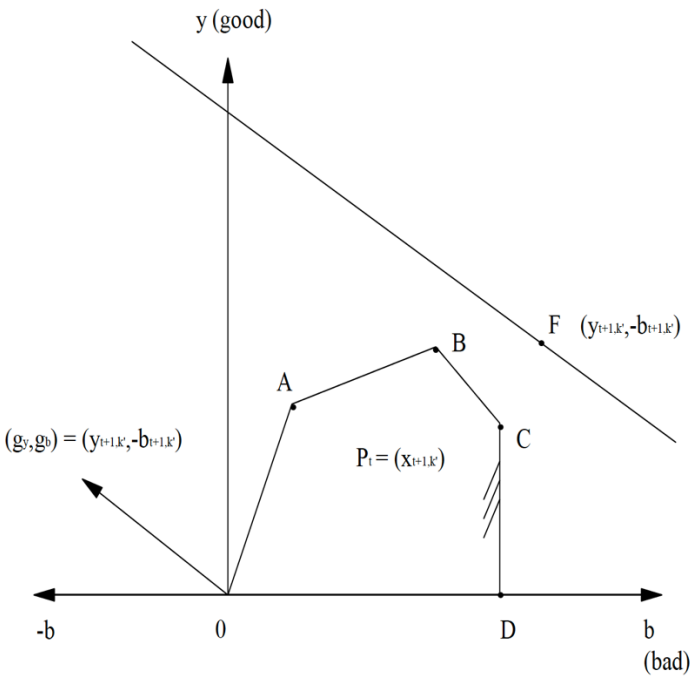


Figure 2. The Directional distance function

Appendix C

Projection into Production Possibility Set under the modified weak disposability assumption.

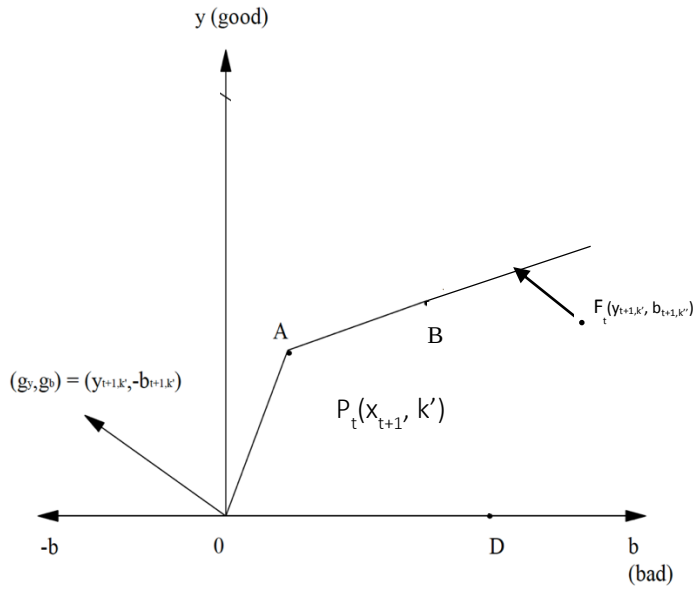


Figure 3. The Directional distance function

Appendix D

We collected the data for period 1995-2017 from *OECD.stat*[6]. Based on the KLEMS standard (capital (K), labor (L), energy (E), materials (M) and service (S) inputs)[7], the technology modeled in this study consists of the following variables:

(1) Capital input. We use the net capital stock in constant prices (price index 2015) in each industry as a proxy of capital stock. OECD STructural ANalysis (STAN) Dataset for Industrial Analysis, provides data for the net capital stock by industry.

(2) Labor input. The total number of employees is used as a proxy for the labor input. *OECD.stat* dataset provides data for labor input by activity.

(3) Intermediate input. We use the Intermediate input in constant prices (price index 2015) in each industry as a proxy for the Energy, Material, and Service input (including any rentals for machinery and equipment). According to the OECD, intermediate inputs represent the value of inputs into processes of production that are consumed within the accounting period.

(4) Desirable (good) output. We use Gross Domestic Production (GDP) in constant prices (price index 2015) as the proxy. *OECD.stat* is our source for data on GDP.

(5) Undesirable (bad) output. Taking into account data availability, we use the two substances emitted in greater quantities by each industry as the proxy. *OECD.stat* offers data on carbon dioxide (tons of pollution) and non-methane volatile organic compounds (tons of pollution) emissions from industrial processes and product.

[6] Link: https://stats.oecd.org/Index.aspx?DataSetCode=STANi4

[7] EU KLEMS is an industry level, growth and productivity research project. Link: https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/eu-klems-capital-labour-energy-materials-and-service_en

The graphs below present the trend of the total manufacturing undesirable outputs (CO2 and MNVOC) and desirable output (GDP) for the period of 1995-2017.

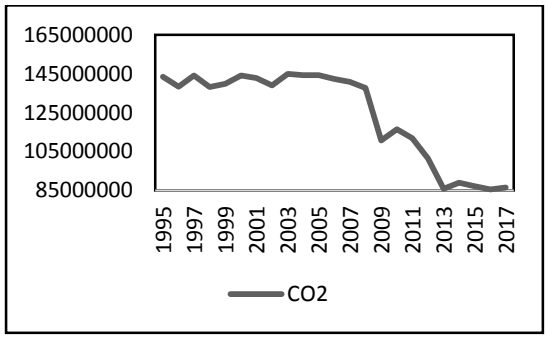


Figure 5. Total CO_2 trend

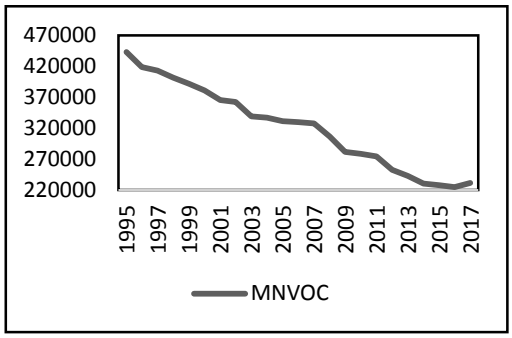


Figure 6. Total MNVOC trend

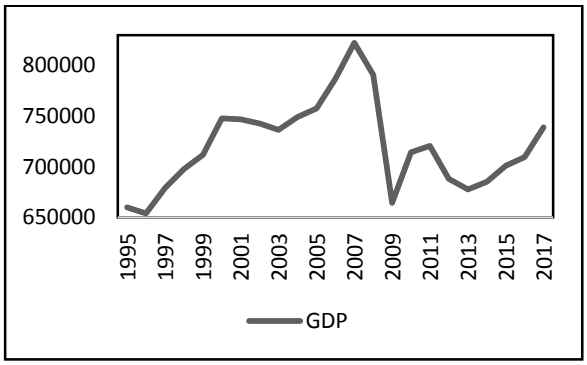


Figure 7. Total GDP trend

Appendix E

Table 5 . Bias-corrected Estimates of MLTCH index

	Food products, beverages and tobacco,	Textiles, wearing apparel, leather and related products,	Wood and paper products; printing	Coke and refined petroleum products	Chemicals and chemical products	Basic pharmaceutical products	Rubber and plastics products, and othe	Basic metals and fabricated metal products	Computer, electronic and optical products	Electrical equipment	Machinery and equipment n.e.c.,	Transport equipment	Other manufacturing; repair and installation of machinery
1995-96	0.9952	0.9699	1.0050	0.9517	0.9831	1.0054	1.0085	0.9983	1.0207	0.9965	1.0086	0.9986	0.9952
1996-97	1.0123	0.9915	1.0020	1.0226	1.0016	1.0026	1.0118	1.0014	0.9702	0.9723	0.9935	1.0087	0.9805
1997-98	0.9897	0.9868	0.9881	0.9600	1.0079	0.9985	1.0019	0.9923	1.0497	1.0227	1.0144	1.0043	0.9896
1998-99	0.9835	0.9564	0.9949	0.9850	0.9849	1.0083	1.0056	0.9956	0.9983	1.0050	1.0092	1.0063	0.9894
1999-00	1.0557	1.0211	0.9999	0.9685	0.9865	1.0056	1.0028	1.0010	0.9794	0.9798	1.0292	1.0180	1.0016
2000-01	0.9788	0.9831	0.9973	0.9675	1.0194*	1.0022	0.9987	1.0026	1.0309	0.9967	1.0088	1.0004	0.9881
2001-02	0.9890	0.9484	0.9902	0.9744	1.0041	1.0005	0.9959	1.0056	0.9841	1.0112	0.9838	1.0086	0.9931
2002-03	1.0253	0.9511	0.9909	0.9966	1.0032	1.0103	0.9953	0.9977	0.9874	1.0037	1.0221	0.9977	0.9816*
2003-04	0.9736	0.9611	1.0020	0.9969	0.9929	1.0040	1.0013	1.0057	1.0234	1.0199	1.0305	1.0128	1.0047
2004-05	1.0267	0.9672	0.9988	1.0123	1.0024	0.9996	0.9991	1.0021	1.0142	1.0012	1.0128	1.0203	1.0001
2005-06	0.9833	0.9828	1.0023	0.9803	1.0181	1.0265*	1.0010	1.0021	1.0313	1.0147	1.0362	1.0539*	1.0075
2006-07	1.0170	1.0342*	0.9997	1.0133	1.0121	1.0174	0.9983	1.0141	1.0221	1.0085	1.0355	1.0548*	1.0025
2007-08	0.9782	0.9063*	0.9899*	0.9945	1.0136	1.0296*	0.9903	1.0003	0.8664*	0.8933*	0.8971*	0.9894	0.9857*
2008-09	0.9823	0.8994*	0.9682*	0.8987*	0.9708*	0.9812	0.9626*	0.9454*	1.0398	0.9893	0.8742*	0.9570*	0.9837
2009-10	1.0239	1.0654	1.0186*	1.0473	1.0410*	1.0612*	1.0168	1.0258*	1.0392	1.0836*	1.0632	1.0717*	1.0010
2010-11	0,9867	1.0275	1.0095	0.9874	1.0298*	1.0652*	1.0032	1.0163*	1.0949*	1.0161	1.0733*	1.0483*	1.0107
2011-12	0.9878	0.9486	0.9849*	0.9972	1.0090	1.0133	0.9875	0.9883	1.0077	0.9969	1.0184	0.9863	0.9846
2012-13	1.0081	0.9644	1.0060	1.0606	1.0114	1.0138	0.9988	1.0030	0.9429	0.9854	0.9651	1.0158	1.0079
2013-14	1.0073	0.9939	1.0020	0.9841	0.9895	0.9866	1.0039	1.0011	1.0241	1.0193	1.0362	1.0541*	1.0048
2014-15	1.0071	0.9657	1.0104	1.0288	1.0180	1.0056	1.0118	1.0011	0.9705	0.9999	0.9481	1.0125	1.0027
2015-16	0.9947	0.9731	0.9982	1.0164	0.9778*	1.0006	1.0003	0.9965	0.9983	1.0155	1.0072	1.0572	1.0152
2016-17	0.9990	0.9862	0.9896	1.0382	1.0104	1.0071	0.9797*	0.9995	1.0008	1.0176	1.0214	1.0344	0.9949

Note: (*) denote significant difference from unit at 0.0

Appendix F

Table 6 . Bias-corrected Estimates of MLECH index

	Food products, beverages and tobacco,.	Textiles, wearing apparel, leather and related products,	Wood and paper products; printing	Coke and refined petroleum products	Chemicals and chemical products	Basic pharmaceutical products	Rubber and plastics products, and othe	Basic metals and fabricated metal products	Computer, electronic and optical products	Electrical equipment	Machinery and equipment n.e.c.,	Transport equipment	Other manufacturing; repair and installation of machinery
1995-96	1.0000	1.0000	1.0018	1.0000	1.0452*	1.0000	0.9935	1.0018	1.0000	1.0000	1.0000	1.0000	1.0000
1996-97	1.0000	1.0000	0.9905	1.0000	1.0004	1.0000	0.9927	0.9981	1.0000	1.0000	1.0000	1.0000	1.0000
1997-98	1.0000	1.0000	1.0150	1.0000	0.9915	1.0000	1.0016	1.0010	1.0000	1.0000	1.0000	1.0000	1.0000
1998-99	1.0000	1.0000	1.0060	1.0000	1.0359*	1.0000	1.0027	1.0044	1.0000	1.0000	1.0000	1.0000	1.0000
1999-00	1.0000	1.0000	0.9959	1.0000	0.9997	1.0000	1.0032	1.0004	1.0000	1.0000	1.0000	1.0000	1.0000
2000-01	1.0000	1.0000	1.0109	1.0000	0.9690*	1.0000	1.0024	0.9954	1.0000	1.0000	1.0000	1.0000	0.9952
2001-02	1.0000	1.0000	1.0024	1.0000	1.0161	1.0000	1.0167	0.9928	1.0000	1.0000	1.0000	1.0000	1.0048
2002-03	1.0000	1.0000	0.9977	1.0000	1.0020	1.0000	0.9927	1.0043	1.0000	1.0000	1.0000	0.9931	1.0022
2003-04	1.0000	1.0000	1.0028	1.0000	1.0135	1.0000	1.0041	0.9985	1.0000	1.0000	1.0000	1.0069	1.0016
2004-05	1.0000	1.0000	0.9948	1.0000	0.9941	1.0000	1.0025	1.0140	1.0000	1.0000	1.0000	0.9809*	1.0012
2005-06	1.0000	1.0000	1.0012	1.0000	0.9915	1.0000	0.9976	1.0140	1.0000	1.0000	1.0000	1.0077	1.0000
2006-07	1.0000	1.0000	1.0003	1.0000	0.9998	1.0000	0.9980	0.9932	1.0000	1.0000	1.0000	1.0000	1.0000
2007-08	1.0000	1.0000	0.9997	1.0000	1.0177	1.0000	0.9943	0.9889	1.0000	1.0000	1.0000	1.0000	1.0000
2008-09	1.0000	1.0000	1.0159	1.0000	0.9209*	1.0000	1.0098	0.9950	1.0000	1.0000	1.0000	1.0000	0.9902
2009-10	1.0000	1.0000	0.9946	1.0000	1.0412*	1.0000	1.0023	1.0039	1.0000	1.0000	1.0000	1.0000	1.0000
2010-11	1.0000	1.0000	1.0001	1.0000	0.9764*	1.0000	0.9928	0.9845*	1.0000	1.0000	1.0000	1.0000	1.0000
2011-12	1.0000	1.0000	1.0129	1.0000	0.9854	1.0000	1.0083	1.0201*	1.0000	0.9765	1.0000	1.0000	1.0000
2012-13	1.0000	1.0000	0.9902	1.0000	0.9932	1.0000	0.9972	0.9996	1.0000	1.0124	1.0000	1.0000	1.0000
2013-14	1.0000	1.0000	1.0027	1.0000	1.0179	1.0000	1.0024	1.0112	1.0000	0.9990	1.0000	1.0000	1.0000
2014-15	1.0000	1.0000	0.9799*	1.0000	1.0033	1.0000	0.9859	0.9994	1.0000	1.0016	1.0000	1.0000	1.0000
2015-16	1.0000	1.0000	1.0112	1.0000	1.0172	1.0000	1.0054	1.0150	1.0000	1.0000	1.0000	1.0000	1.0000
2016-17	1.0000	1.0000	1.0055	1.0000	1.0125	1.0000	1.0279	1.0005	1.0000	0.9859	1.0000	1.0000	1.0000

Note: (*) denote significant difference from unit at 0.05