Technological Forecasting & Social Change 184 (2022) 121993

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

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

Daniela Lena [a], Carl A. Pasurka [b], Marco Cucculelli [a,*]

[a] Department of Economics and Social Science, Marche Polytechnic University, Piazzale Martelli 8, 60121 Ancona, Italy
[b] Schar School of Policy and Government - George Mason University, Arlington VA United States

ARTICLE INFO

JEL classification:
D24
O13
O44
Q56

Keywords:
Environmental regulation
Productivity growth
Direction distance function
Malmquist-Luenberger index
Manufacturing industry
Italy

ABSTRACT

Environmental policy is at the core of the current research debate and policy action. Few studies have discussed the impact of environmental regulation on productivity growth at industry level, and the empirical evidence on this issue is still controversial. Based on panel data on thirteen Italian manufacturing industries from 1995 to 2017, this study analyzes the effect of environmental policies on sectoral productivity by measuring the adjusted productivity growth using the Malmquist-Luenberger index. The main result of this analysis is that environmental regulation has no negative effect in most of the sample industries. A bootstrapping approach has been used to assess the robustness of estimated results.

1. Introduction

In the process of economic development, environmental governance is an issue that each country should prioritize for reaching a sustainable economic growth. Policymakers, academics, industrial practitioners and firms are recognizing that environmental degradation has become a worldwide concern, and more emphasis should be put on minimizing environmental issues related to economic growth. Also, the awareness on household's activities that generate waste and damage to the environment is significant (Sakai et al., 2017). In this scenario, policymakers are committed to improve the quality of the environment by limiting the overconsumption of natural capital and preventing emissions generated by production processes (Yu et al., 2017).

The manufacturing industry is one of the major contributors to environmental degradation: therefore, the pressure to minimize its environmental influence is becoming paramount nowadays (Kraus et al., 2020). To overcome the environmental issue, industrial processes must move towards activities that ensure energy saving, reduce waste and pollution, limit the consumption of water and promote the design of eco-friendly products (Singh et al., 2020; Rehman et al., 2021). Corporates headquarters and small manufactures are required to conduct business in a new way, that integrates environmental, social, and economic concerns in the business strategy (Hernández et al., 2020). However, gaining sustainable industrial production processes and green growth can generate additional costs to firms, which could directly affect their economic viability. In this context, designing the appropriate environmental policy is crucial for reaching and maintaining competitive advantages and balanced growth (Liang et al., 2022; Rehman et al., 2022; Wang et al., 2019). Indeed, if the costs caused by environmental activities are comparatively high, they may adversely affect firm behavior and slow down the propensity of firms to renew their products and innovate their business models. As a consequence, competitiveness and productivity growth may even decline and drive heavy-polluting firms to delocalize towards countries with the less stringent environmental policy (Rubashkina et al., 2015; Albrizio et al., 2017).

Environmental policy is at the core of the current research and policy discussions, as it affects firms' competitiveness and overall productivity by imposing costs to the firms while benefitting the environment (Knights et al., 2014; Huiban et al., 2018; Herman and Shenk, 2021). Despite the huge attention paid to this trade-off (Conrad and Wastl, 1995; Dufour et al., 1998; Berman and Bui, 2001; Gray and Shadbegian, 2003; Lanoie et al., 2008; Becker, 2011; Lee et al., 2015; Manello, 2017;

* Corresponding author.
E-mail address: m.cucculelli@univpm.it (M. Cucculelli).

https://doi.org/10.1016/j.techfore.2022.121993
Received 14 March 2022; Received in revised form 26 July 2022; Accepted 24 August 2022
Available online 6 September 2022

Peng, 2020), the impact of environmental regulations on overall productivity performance is still an open issue (De Santis et al., 2020), mainly because empirical findings are very context-specific and the contexts of analysis are very different (Cai and Ye, 2020). Moreover, among the studies that deal with the nexus between environmental regulation and productivity growth, the vast majority is focused on international comparisons across countries (Domazlicky and Weber, 2001; Alpay et al., 2002; Yörük and Zaim, 2005; Aiken et al., 2009; Rubashkina et al., 2015; Albrizio et al., 2017; Hille and Möbius, 2018; Beltrán-Esteve et al., 2019), which indeed might further weaken the understanding of the issue, given of the heterogeneous policy mix that characterizes different countries (Brunel and Levinson, 2016; Dechezleprêtre and Sato, 2017).

In this framework, the paper aims at evaluating the trade-off between environmental regulation and productivity growth at sectoral level in an economy where the manufacturing industry has a central role. The Italian manufacturing industry and its constituting sectors provide a unique setting that alleviates the issue of heterogeneity caused by cross-country comparison. Moreover, even though the Italian economy has been under environmental regulatory pressure for a long time, no studies have addressed the trade-offs between environmental policy and productivity at the sector level, a drawback that we address by providing first-hand evidence for thirteen sectors within the manufacturing industry.

On the empirical side, we follow the approach proposed by Chung et al. (1997), who used the Joint Production Model (JPM) and the Malmquist index to develop a new index, the Malmquist-Luenberger (ML) index, that models the joint production of good (desirable) and bad (undesirable) outputs.[1] This index can be decomposed into two indices that explain technical change, i.e., shifts in the production frontier, and changes in technical efficiency, i.e., changes in distance of an observation from the production frontier.[2] We operationalize the model by applying the Malmquist-Luenberger index to a panel data set of 13 Italian manufacturing industries, using a three-output/three-input technology for the period from 1995 to 2017. To determine if the environmental regulation influences the productivity growth, we compare ML index to the traditional M index.

As for the measurement issue, even though the Malmquist-Luenberger index (ML) proposed by Chung et al. (1997) is a popular solution for calculating TFP growth, researchers are still facing with the problem of infeasible solution. The early solutions to minimize this issue included the use of multiple year windows of data (Färe et al., 2001; Kumar, 2006; Färe et al., 2007), the global Malmquist-Luenberger productivity index (Oh, 2010), the sequential Malmquist-Luenberger index (Krautzberger and Wetzel, 2012), the biennial Malmquist–Luenberger productivity index (Du et al., 2014) and the uses of the Data Envelopment Analysis (DEA) slacks-based model (Arabi et al. (2015). Some researchers (Färe et al., 2014; Färe et al., 2016; Du et al., 2019) recommended to apply a modification of the undesirable outputs constrains to eliminate the infeasible problem. Thus, we deal with this issue by introducing a modification of the weak disposability assumption that imposes a less than or equal to constraint ("≦") to the undesirable outputs, not used previously for calculating the ML index within the DEA model.

This paper makes two main contributions. First, we improve the general framework of analysis of the impact of regulation on TFP by removing the negative influence of the infeasible problem in the application of DEA models in a sectoral context. In this regard, the paper provides an extension of the basic modelling approach used to address the measurement of TFP at sector level. Second, this study offers direct evidence on the nexus between environmental regulation and productivity growth at sectoral level in a manufacturing-intensive European economy, thus giving policymakers valuable information to design better environmental industrial policies.

The rest of the paper is organized as follows. Section 2 provides a review of the literature on the effect of environmental regulations on the productivity growth in the manufacturing sector. This Section is followed by the description of the productivity index and the model of analysis. Section 4 discusses the data and the results. Section 5 provides some statistical results from bootstrapping and Section 6 concludes.

2. Literature background

Climate Action and the new plan "fit for 55" recently proposed by the European Commission have forced EU governments to revise and intensify their environmental policies. The debate on environmental regulations has two principal concerns. First, there are concerns about whether the regulations are optimal in the sense that marginal benefits equal marginal costs. Second, there are concerns about the impact of regulation on productivity and competitiveness. The conventional hypothesis suggests that imposing regulations on business activity results in higher production costs and declining competitiveness of nations or industries subject to those environmental regulations (Pasurka, 2008). However, imposing environmental regulation pushes firms to move towards sustainable production by investing in new emission-reducing technologies (Cui et al., 2022; Wang et al., 2022). In this framework, the empirical relationship between environmental regulation, productivity performance and economic growth is still an open and unsettled issue (e.g., Manello, 2017; Wang and Shao, 2019; Peng, 2020; Song et al., 2021; Sun et al., 2021; Hille and Möbius, 2018), even if a positive relationship has been found at the international level, but not at the industry- and the firm-level of analysis (Cohen and Tubb, 2018). Several empirical studies have examined the consequences of environmental regulation using national data (e.g., Meyer, 1992; Meyer, 1996: Yörük and Zaim, 2005; Kumar, 2006; Wu and Wang, 2008; Oh and Heshmati, 2010; Hille and Möbius, 2018; Beltrán-Esteve et al., 2019; Wang et al., 2019), regional data (e.g., Chang and Hu, 2010; Du et al., 2014; Miao et al., 2019; Chen et al., 2021) and firm-level data (e.g., Chung et al., 1997; Hernandez-Sancho et al., 2000; Berman and Bui, 2001; Gray and Shadbegian, 2003; Yu et al., 2008; He et al., 2013; Lee et al., 2015; Tang et al., 2020), but only a few have considered the single-industry level. Thus, the focus of the remaining literature review will be on empirical studies at the industry level.

Early studies reviewed by Gray (1987) and Barbera and McConnell (1990) found that pollution abatement costs were associated with a negative effect on the multi factor productivity of the manufacturing sector in the USA. 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 manufacturing industry in Quebec and found declining total factor productivity. 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 that adjusted productivity in manufacturing showed a 1.4 % annual growth rate. The authors pointed 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

[1] The initial efforts to incorporate bad output in economic growth analysis were undertaken by 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 (M) index, together with the assumption of the direction vector proposed by Luenberger in 1992.

[2] Different researchers have used the Malmquist index (Zhou et al., 2010; Sueyoshi and Goto, 2013; Essid et al., 2014; Fuentes and Lillo-Banuls, 2015) and Malmquist-Luenberger index (Zhang et al., 2011; Krautzberger and Wetzel, 2012; Du et al., 2014; Lee et al., 2015; Du et al., 2018) to measure the TFP changes and to evaluate the effect of the environmental regulation on TFP.

1987 to 1997 and calculated the total factor productivity for manufacturing industries in Taiwan. She found environmental regulations overall had a positive effect on industry productivity for all Taiwan manufacturing sectors. In his study on manufacturing sectors in Japan, Hamamoto (2006) found an indirect positive effect of the environmental regulation on productivity growth through higher R&D expenditure. Lanoie et al. (2008) investigated the effect of environmental regulations on total factor productivity in the Quebec manufacturing sector: using a sample of seventeen industries in the period 1985–1994, the authors found that environmental regulations have a negative effect on TFP. In their investigation on eight manufacturing industries in Japan, Germany, the Netherlands and the United States, Aiken et al. (2009) found that there were negligible effects for Japanese and Dutch manufacturing industries, while annual productivity growth declined by 0.11 % for the United States and increased by 0.24 % 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 caused a decrease in productivity of the EU transport industry. Yang et al. (2012) in their study on manufacturing sectors in Taiwan found that stringent environmental regulations have a positive effect on TFP growth. In a recent study, Chen et al. (2018) investigated 36 industrial sectors in China from 2000 to 2014. According to their study, industrial adjusted total factor productivity (TFP) declined by 0.02 % per year on average.

Different studies that address the policy-productivity trade-off have extended the analysis to cross-country, multi-sector analysis. Rubashkina et al. (2015) utilized data for nine manufacturing industries in seventeen European countries, excluding France, Germany, and Italy. They have not found any relationship between environmental regulation and productivity growth. Albrizio et al. (2017) conducted a study on ten manufacturing industries among seventy OECD countries and found a positive effect of the environmental policy on productivity growth. Similarly, Franco and Marin (2017) conducted a study on thirteen manufacturing industries among eight European countries and found a positive effect of environmental regulation on productivity growth. Exploring a panel data of 14 manufacturing sectors across 28 OECD countries, Hille and Möbius (2018) found that an increase in environmental policy stringency has a positive effect on productivity growth.

Overall, at least in the strand of the literature that considers the manufacturing sector and its associated sectors, the policy-productivity nexus as a determinant of the economic growth is still largely unresolved and needs to be studied further (Behun et al., 2018).[3] To the best of our knowledge, there is not any study on the productivity of Italian manufacturing industries that takes into consideration environmental regulation issues. In the context of the Sustainable Economic Development Plan proposed by the Italian government, emphasis has been put on the environmental protection. Italy has made substantial progress in reducing air emissions: according to the ISPRA (*Istituto Superiore per la Protezione e la Ricerca Ambientale*),[4] the level of CO_2 emissions from manufacturing and construction sectors decreased by 44 % from 1990 to 2018. Although the Italian economy has been under environmental regulatory pressure from the early 1970s (Fisher, 2017), only a few studies have addressed this issue and most of these studies have used aggregate data (e.g., Jeon and Sickles, 2004; Beltrán-Esteve et al., 2019). Likewise, no studies have been found at the sector level, an area where the paper strives to contribute by analyzing the effect of environmental regulations on productivity growth for thirteen manufacturing industries.

3. Methodology

3.1. 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 direction 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 build on the standard framework proposed by Chung et al. (1997). The first assumption is related to the production set. The production set P^t for each time period $t = 1, \ldots\ldots, T$ transforms the inputs $x^t \in R_+^{\ N}$ into outputs, goods $y^t \in R_+^{\ M}$ and bads $b^t \in R_+^{\ I}$:

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

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, weak disposability of outputs is imposed in the general framework, i.e.,:

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

This condition states that a reduction of undesirable outputs can be achieved through 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:

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

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 is not for the undesirable output when there are environmental policies. The assumption that the good outputs are freely disposable is constructed as follow:

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

Together, Eq. (2) and Eq. (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 the "null-joint" property. In other words, an output cannot be produced without the other, i.e.,:

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

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

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

where β is the maximum feasible expansion of the good output and contraction of the bad output. The maximum expansion and contraction

[3] Industry accounts for a major part of the European economy, generating 24 % of GDP and employing up to 50 million people, representing one out of five jobs in the EU. Link: https://data.worldbank.org/indicator/NV.IND.MANF.ZS?locations=EU.

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

of output 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.[5] Chung et al. (1997) output-oriented Malmquist–Luenberger productivity index between periods t and $t+1$ is defined as:

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

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:

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

and

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

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 the index is greater than one, $ML_0^{t\ t+1} > 1$ and a decrease in productivity if it 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, it indicates there is no shift in the production possibilities frontier. If the $MLTCH_t^{t+1}$ index is less than unity, it 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 frontier. If efficiency changes exceed unity (less than unity), it indicates that the observation is closer (further) to the frontier in period $t+1$ than it was in period t. An efficiency index (MLECH) equal to unity indicates that the observation is at 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:

$$\overrightarrow{D}_0^t(x^t(k'), y^t(k'), b^t(k'); y^t(k'), -b^t(k')) = Max\ \beta(k') \quad (11)$$

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

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

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

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

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.[6] 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, $\overrightarrow{D}_0^{t,t}$, $\overrightarrow{D}_0^{t,t+1}$, $\overrightarrow{D}_0^{t+1,t}$, $\overrightarrow{D}_0^{t+1,t+1}$, which measure distance of an observation to the frontier (see Appendix A). The distance functions for the mixed- period LP problems, $\overrightarrow{D}_0^{t,t+1}$, $\overrightarrow{D}_0^{t+1,t}$, 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 an 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 to constraint on the undesirable outputs. This

[5] Briec (1997) specifies a distance function for the growth of the technology like Luenberger's shortage function. See Luenberger (1992a, 1992b, 1994a, 1994b, 1995a, 1995b).

[6] 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.

assumption was firstly introduced by the authors for eliminating the possibility of a downward sloping of the frontier. This modified specification assumes that when the good output is optimal, it wouldn't be affected by producing fewer undesirable outputs and could also avoid the slack problem of equality for bad output sets effectively (Du et al., 2019). 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 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:

$$\vec{D}^{t}_{0}(\mathrm{x}^{t}(\mathrm{k}^{'}),\mathrm{y}^{t}(\mathrm{k}^{'}),\mathrm{b}^{t}(\mathrm{k}^{'});\mathrm{y}^{t}(\mathrm{k}^{'}),-\mathrm{b}^{t}(\mathrm{k}^{'}))=Max\ \beta(\mathrm{k}^{'}) \tag{12}$$

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

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

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

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

where the mixed- period LP problem resembles Eq. (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).

3.2. Data and variables

Operationalizing the model and calculating the total factor productivity requires information on input quantities as well as good and bad output quantities. From the classical economists' studies, the standard variable used for measuring the TFP are, the capital stock, the number of employees, and the GDP. Several studies have improved the TFP estimations by introducing different variables like labor productivity (Sarbu, 2017; Feng et al., 2018), sustainability (Husniah and Supriatna, 2016; Liu et al., 2016; Wei et al., 2020; Zhang et al., 2020), knowledge proxies (Hidalgo and Hausmann, 2009; Elmawazini, 2014; Bhattacharya et al., 2021), and energy (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Wooldridge, 2009; Ackerberg et al., 2015; Mirza et al., 2021). In the environmental context, different authors have used air emission as an additional variable to measure the green total factor productivity (Tzouvelekas et al., 2007; Chung et al., 1997; Färe et al., 2014: Lee et al., 2015; Färe et al., 2016; Wang and Shen, 2016; Wu et al., 2019; Zhang and Jiang, 2019). Thus, we use capital stock, the number of employees, GDP, and air emissions for Italian manufacturing industries to measure the green total factor productivity and, following Chen et al. (2018) and Silveira et al. (2021), we use intermediate input as a proxy for energy consumption, material, and service.[7] We obtain the information from the OECD website, OECD STructural ANalysis (STAN) Dataset for Industrial Analysis.[8] 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.

4. Results

Our sample consists of a balanced panel of 13 manufacturing industries for the period from 1995 to 2017.[9] Table 1 presents summary statistics for our sample, while Appendix D provides information about the desirable output, undesirable outputs, and inputs.

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. 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 % annual productivity decline for Textiles, Wearing apparel, Leather products industry (C13-C15), to a high of a 1.8 % annual growth rate for Transport equipment industry (C29-C30).

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

[7] The intermediate inputs include all the inputs (others from capital and labor) that are consumed during the production process. These inputs include energy, materials, and service (including any rentals for machinery and equipment) (OECD, 2001).

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

[9] 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).

Table 1
Descriptive statistic (millions).

Year	Variable	Units	Mean	Std. dev.	Minimum	Maximum
1995	Gross output	Euro	65,789.15	35,528.54	12,522.5	119,755.4
	Carbon Dioxide (CO_2)	Tonnes	1.39e+07	240,008	4.18e+07	1.39e+07
	NMVOC	Tonnes	22,392.7	4735	82,038	22,392.7
	Hours worked-employees	Hours	3.657.413	430.442	1.313.856	3.657.413
	Net Capital Stock	Euro	14,268.94	6.613.189	48,723.97	14,268.94
	Intermediate input	Euro	27,161.04	7.565.221	94,309.69	27,161.04
2017	Gross output	Euro	73,595.38	41,331.01	21,873.77	142,963.2
	Carbon Dioxide (CO_2)	Tonnes	6,653,660	8,041,646	228,084	2.49e+07
	NMVOC	Tonnes	17,795	12,588.41	1721	43,963
	Hours worked-employees	Hours	4.480.506	2.964.953	268.961	9.894.484
	Net Capital Stock	Euro	37,370.48	17,102.3	16,205.69	67,613.14
	Intermediate input	Euro	54,077.92	31,314.34	13,848.35	111,892.6

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

Table 2
Decomposition of average annual changes, 1995–2017.

	ISIC (Rev.4)	Malmquist-Luenberger			Malmquist		
		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	10,017	0.9997	0.9980	1.0017
Basic pharmaceutical products and pharmaceutical preparations	C21	1.0110	10,110	1.0000	1.0028	1.0028	1.0000
Rubber and plastics products, and other non-metallic mineral products	C22-C23	10,003	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**

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). In this industry, both productivity (ML) and its decomposition (MLTCH and MLECH) are not affected by environmental regulations.

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 % 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 year, while for the ML index, Chemicals and chemical products industry (C20) shows the highest MLECH, i.e., 0.17 %.

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

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

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 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 % in 2008–2009 to a high of 4.60 % in 2009–2010. Under Malmquist index, the annual change in productivity growth ranges from an increase of 2.70 % in 2009–2010 to a 5.41 % 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.

Changes in efficiency for the ML index range from an increase of 0.40 % for both 1998–1999 and 2015–2016, to a 0.52 % decline for 2008–2009, while technical change ranges from −4.31 % in 2008–2009 to 4.27 % in 2009–2010. The change in efficiency, for the M index, ranges from 0.81 % in 2015–2016 to −0.96 % for 2010–2011, while technical change posted growth from 2.57 % in 2009–2010 to −4.66 % 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-practice 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, 2000b) and developed for estimating the sampling distribution and confidence intervals for the Malmquist index (Simar and Wilson, 1999). 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, 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 et al. (2015), we adopt` the bootstrapping approach of Hampf (2013) to test the reliability of our result. To determine whether changes in productivity growth, efficiency or technical change are statistically significant, we use a 95 % 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) from the bootstrapping, it is difficult to point out if efficiency change or technological change is driving the productivity change. The disaggregated indices for most of the industries do not show statistically significant change. However, we find some period where the MLTCH show significant changes, which are mainly concentrated in the period 2006–2011. The result of bias-corrected MLTCH and MLECH indexes are provided in Appendix E and Appendix F.

6. Conclusions

The aim of our work is to examine the role of the environmental regulation on productivity growth at industrial level. We focus our analysis on measuring adjusted productivity growth in Italian manufacturing industries when both desirable and undesirable outputs are taken into consideration. Using a dataset of thirteen manufacturing industries between 1995 and 2017, a ML productivity index is used 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 % 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 % 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 only marginally affected in all other industries. Indeed, the results provided by bootstrapping the index show that there is significant aggregate productivity change for almost all industries. Bootstrapping confirms

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*

[*] Denote significant difference from unit at 0.05.

the robustness of the overall analysis and shows that a significant aggregate productivity growth has been observed in the ML index during the period 1995–2017.

6.1. Theoretical and practical implications

This study contributes to the current literature on the evaluation of the environmental policy by providing an operative solution to the infeasible problem which is usually found in the common methodological approach. Specifically, we improve the general framework of analysis of the impact of regulation on productivity by removing the negative influence of the infeasible problem in the application of DEA models in a sectoral context. On the practical side, we expect these results can provide valuable information to practitioners, researchers, and industrial policymakers, and help them in designing better environmental policies. Corporate managers and policymakers can use the present research as a reference framework to further extend current policies for gaining environment-compliant competitive advantages.

6.2. Policy recommendation

Even though the existing environmental policy has improved the quality of the environment by reducing CO_2 emissions, additional policy interventions should be considered in the future in order to achieve new targets set by the European Commission and, in general, gain sustainable growth. Attention should be paid to two main aspects. On the one hand, additional policy actions should be undertaken to encourage investments in *green* technologies capable of shifting the production technology (i.e., production frontier) in the direction of fewer undesirable outputs and more good output. The focus of the policy should be on increasing and reforming public innovation budgets in *green* technologies and promoting international agreements on investment in green technologies. On the other hand, policymakers should focus on activities that promote the combination of novel *green* technologies with traditional production processes. To catch-up with the best-available production technology (i.e., production frontier), policy actions targeted to expand the markets for green products and services and design fiscal measures that penalize polluters and subsidy the use of green practices can be planned and implemented.

6.3. Limitation and future research

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. Second, 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. Third, the model only partially accounts for productivity differences across industries (i.e., the composition effect), whereas several scholars have stressed 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 using more detailed and larger datasets.

Declaration of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.techfore.2022.121993.

References

Ackerberg, D., Caves, K., Frazer, G., 2015. Identification properties of recent production function estimators. Econometrica 83 (6), 2411–2451.
Aiken, D.V., Färe, R., Grosskopf, Sh., Pasurka, C., 2009. Pollution abatement productivity growth: evidence from Germany, Japan, the Netherlands, and the United States. Environ. Resour. Econ. 44, 11–28.
Albrizio, S., Kozluk, T., Zipperer, V., 2017. Environmental policies and productivity growth: evidence across industries and firms. J. Environ. Econ. Manag. 81, 209–226.
Alpay, E., Buccola, S., Kerkvliet, J., 2002. Productivity growth and environmental regulation in Mexican and U.S. food manufacturing. Am. J. Agric. Econ. 84 (4), 887–901.
Arabi, B., Munisamy, S., Emrouznejad, A., 2015. A new slacks-based measure of Malmquist-Luenberger index in the presence of undesirable outputs. Omega 51, 29–37.
Ayres, R.U., Kneese, A.V., 1969. Production, consumption & externalities. Am. Econ. Rev. 59, 282–296.
Barbera, A.J., McConnell, V.D., 1990. The impact of environmental regulations on industry productivity: direct and indirect effects. J. Environ. Econ. Manag. 18 (1), 50–65.
Baumol, W.J., Blackman, S.A.B., Wolf, E.N., 1989. Productivity and American Leadership. MIT Press, Cambridge.
Becker, R.A., 2011. Local environmental regulation and plant-level productivity. Ecol. Econ. 70 (12), 2516–2522. https://doi.org/10.1016/j.ecolecon.2011.08.019.
Behun, M., Gavurova, B., Tkacova, A., Kotaskova, A., 2018. The impact of the manufacturing on the economic cycle of the European Union countries. J.Compet. 10 (1), 23.
Beltrán-Esteve, M., Giménez, V., Andrés, J., Picazo-Tadeo, J.A., 2019. Environmental productivity in the European Union: a global Luenberger-meta frontier. Sci. Total Environ. 692, 136–146.
Berman, E., Bui, L., 2001. Environmental regulation and productivity: evidence from oil refineries. Rev. Econ. Stat. 83 (3), 498–510.
Bhattacharya, M., Okafor, L.E., Pradeep, V., 2021. International firm activities, R&D, and productivity: evidence from Indian manufacturing firms. Econ. Model. 97, 1–13.
Briec, W., 1997. A graph-type extension of Farrell technical efficiency measure. J. Prod. Anal. 8, 95–110.
Brunel, C., Levinson, A., 2016. Measuring the stringency of environmental regulations. Rev. Environ. Econ. Policy 10 (1), 47–67.
Cai, W., Ye, P., 2020. How does environmental regulation influence enterprises'total factor productivity? A quasi-natural experiment based on China's new environmental protection law. J. Clean. Prod. 276, 124105.
Chang, T., Hu, J., 2010. Total-factor energy productivity growth, technical progress, and efficiency change: an empirical study of China. Appl. Energy 87 (10), 3262–3270.
Chen, C., Lan, Q., Gao, M., Sun, Y., 2018. Green total factor productivity growth and its determinant in China's industrial economy. Sustain.J.MDPI 10, 1052.
Chen, Y., Miao, J., Zhu, Z., 2021. Measuring green total factor productivity of China's agricultural sector: a three-stage SBM-DEA model with non-point source pollution and CO2 emissions. J. Clean. Prod. 318, 128543.
Cheng, G., 2014. Data Envelopment Analysis: Methods and MaxDEA Software [in Chinese]. Intellectual Property Publishing House Co., Ltd, Beijing.
Chenery, H., Syrquin, M., 1975. Patterns of Development 1950–70. Oxford University Press, Oxford.
Chung, Y.H., Färe, R., Grosskopf, S., 1997. Productivity and undesirable output: a directional distance function approach. J. Environ. Manag. 51, 229–240.
Conrad, K., Wastl, D., 1995. The impact of environmental regulation on productivity in German industries. Empir. Econ. 20 (4), 615–633.
Cohen, M.A., Tubb, A., 2018. The impact of environmental regulation on firm and country competitiveness: a meta-analysis of the Porter hypothesis. J. Assoc. Environ. Resour. Econ. 5 (2), 371–399.
Cui, J., Dai, J., Wang, Z., Zhao, X., 2022. Does environmental regulation induce green innovation? A panel study of Chinese listed firms. Technol. Forecast. Soc. Chang. 176, 121492.
De Santis, R., Esposito, P., Jona-Lasinio, C., 2020. Environmental regulation and productivity growth: main policy challenges. LSE 'Europe in Question' Discussion Paper Series, paper 158. Link. https://www.lse.ac.uk/european-institute/Assets/Documents/LEQS-Discussion-Papers/LEQSPaper158.pdf.
Dechezleprêtre, A., Sato, M., 2017. The impacts of environmental regulations on competitiveness. Rev. Environ. Econ. Policy 11 (2), 183–206.
Domazlicky, B., Weber, W.L., 2001. Productivity growth and pollution in state manufacturing. Rev. Econ. Stat. 83 (1), 195–199.
Du, M., Wang, B., Wu, Y., 2014. Sources of China's economic growth: an empirical analysis based on the BML index with green growth accounting. Sustainability 6 (9), 5983–6004.

Du, J., Chen, Y., Huang, Y., 2018. A modified Malmquist-Luenberger productivity index: assessing environmental productivity performance in China. Eur. J. Oper. Res. 269, 171–187.
Du, J., Duan, Y., Xu, J., 2019. The infeasible problem of Malmquist-Luenberger index and its application on China's environmental total factor productivity. Ann. Oper. Res. 278, 235–253. https://doi.org/10.1007/s10479-017-2603-3.
Dufour, C., Lanoie, P., Patry, M., 1998. Regulation and productivity. J. Prod. Anal. 9 (3), 233–247.
Elmawazini, K., 2014. FDI spillovers, efficiency change and host country labor productivity: evidence from GCC countries. Atl. Econ. J. 42 (4), 399–411.
Essid, H., Ouellette, P., Vigeant, S., 2014. Productivity, efficiency, and technical change of Tunisian schools: a bootstrapped Malmquist approach with quasi-fixed inputs. Omega 42 (1), 88–97.
Färe, R., Grosskopf, S., 1996. Intertemporal Production Frontiers: With Dynamic DEA. Kluwer Academic Publishers, Boston.
Färe, R., Grosskopf, S., Pasurka, C.A., 2001. Accounting for air pollution emissions in measuring of state manufacturing productivity growth. J. Reg. Sci. 41 (3), 381–409.
Färe, R., Grosskopf, S., Pasurka, C.A., 2007. Environmental production functions and environmental directional distance functions. Energy 32 (7), 1055–1066.
Färe, R., Grosskopf, S., Pasurka, C.A., 2014. Potential gains from trading bad outputs: the case of U.S. electric power plants. Resour. Energy Econ. 36, 99–112.
Färe, R., Grosskopf, S., Pasurka, C.A., 2016. Technical change and pollution abatement costs. Eur. J. Oper. Res. 48, 715–724.
Feng, J.C., Huang, M.B., Wang, M., 2018. Analysis of green total-factor productivity in China's regional metal industry: a meta-frontier approach. Resour.Policy 58, 219–229.
Fisher, E., 2017. Environmental Law. A Very Short Introduction. Oxford University Press, US.
Franco, C., Marin, G., 2017. The effect of within-sector, upstream and downstream environmental taxes on innovation and productivity. Environ. Resour. Econ. 66 (2), 261–291.
Fuentes, R., Lillo-Banuls, A., 2015. Smoothed bootstrap Malmquist index based on DEA model to compute productivity of tax offices. Expert Syst. Appl. 42 (5), 2442–2450.
Gray, W.B., 1987. The cost of regulation: OSHA, EPA and the productivity slow down. Am. Econ. Rev. 77 (5), 998–1006.
Gray, B.W., Shadbegian, J.R., 2003. Plant vintage, technology, and environmental regulation. J. Environ. Econ. Manag. 46 (3), 384–402.
Hamamoto, M., 2006. Environmental regulation and the productivity of Japanese manufacturing industries. Resour. Energy Econ. 28 (4), 299–312.
Hampf, B., 2013. Nonparametric Efficiency Analysis in the Presence of Undesirable Outputs [Ph.D. Thesis]. Available at:. Technische Universität, Darmstadt https://tuprints.ulb.tu-darmstadt.de/3303/.
He, F., Zhang, Q., Lei, J., Fu, W., Xu, X., 2013. Energy efficiency and productivity change of China's iron and steel industry: accounting for undesirable outputs. Energy Policy 54, 204–213.
Herman, S.K., Shenk, J., 2021. Pattern discovery for climate and environmental policy indicators. Environ. Sci. Policy 120, 89–98.
Hernández, J.P.S.-I., Yañez-Araque, B., Moreno-García, J., 2020. Moderating effect of firm size on the influence of corporate social responsibility in the economic performance of micro-, small-and medium-sized enterprises. Technol. Forecast. Soc. Chang. 151, 119774.
Hernandez-Sancho, F., Picazo-Tadeo, A., Reig-Martinez, E., 2000. Efficiency and environmental regulation: an application to Spanish wooden goods and furnishings industry. Environ. Resour. Econ. 15, 365–378.
Hidalgo, C.A., Hausmann, R., 2009. The building blocks of economic complexity. Proc. Natl. Acad. Sci. U. S. A. 106 (26), 10570–10575.
Hille, E., Möbius, P., 2018. Environmental policy, innovation, and productivity growth: controlling the effects of regulation and endogeneity. Environ. Resour. Econ. 73, 1315–1355. https://doi.org/10.1007/s10640-018-0300-6.
Huiban, J.P., Mastromarco, C., Musolesi, A., Simioni, M., 2018. Reconciling the Porter hypothesis with the traditional paradigm about environmental regulation: a non-parametric approach. J. Product. Anal. 50 (3), 85–100.
Husniah, H., Supriatna, A.K., 2016. Optimal number of fishing fleet for a sustainable fishery industry with a generalized logistic production function. In: Proceedings of 2015 International Conference on Industrial Engineering and Systems Management, IEEE IESM 2015, 7380211, pp. 546–554.
Jeon, M.B., Sickles, C.R., 2004. The role of environmental factors in growth accounting. J. Appl. Econ. 19, 567–591.
Knights, A.M., Culhane, F., Hussain, S.S., Papadopoulou, K.N., Piet, G., Raakær, J., Rogers, S.I., Robinson, L.A., 2014. A stepwise process of decision-making under uncertainty when implementing environmental policy. Environ. Sci. Policy 39, 56–64.
Kraus, S., Rehman, S.-U., García, F.J.S., 2020. Corporate social responsibility and environmental performance: the mediating role of environmental strategy and green innovation. Technol. Forecast. Soc. Chang. 160, 120262.
Krautzberger, L., Wetzel, H., 2012. Transport and CO2: productivity growth and carbon dioxide emissions in the European commercial transport industry. Environ.Resour. Econ. 53, 435–454. https://doi.org/10.1007/s10640-012-9569-z.
Kumar, S., 2006. Environmentally sensitive productivity growth: a global analysis using Malmquist-Luenberger index. Ecol. Econ. 56 (2), 280–293.
Kuznets, S., 1971. Economic Growth of Nations, Total Output and Productive Structure. Harvard University Press, Cambridge.
Lanoie, P., Patry, M., Lajeunesse, R., 2008. Environmental regulation and productivity: testing the porter hypothesis. J. Prod. Anal. 30 (2), 121–128. http://www.jstor.org/stable/41770359.
Lee, B.L., Wilson, C., Pasurka, C.A., 2015. The good, the bad, and the efficient: productivity, efficiency, and technical change in the airline industry, 2004–11. J. Transp. Econ. Policy 49 (2), 338–354 (17).
Leontief, W., 1970. In: Environmental Repercussions and the Economic Structure: An Input-Output. Approach the Review of Economics and Statistics, 52(3), pp. 262–271.
Levinsohn, J., Petrin, A., 2003. Estimating production functions using inputs to control for unobservables. Rev.Econ.Stud. 70, 317–342.
Liang, T., Zhang, Y., Qiang, W., 2022. Does technological innovation benefit energy firms'environmental performance? The moderating effect of government subsidies and media coverage. Technol. Forecast. Soc. Chang. 180, 121728.
Liu, B.G., Wang, B., Zhang, N., 2016. A coin has two sides: which one is driving China's green TFP growth? Econ. Syst. 40 (3), 481–498.
Luenberger, D.G., 1992a. Benefit functions and duality. J. Math. Econ. 21, 461–486.
Luenberger, D.G., 1992b. New optimality principal for economic efficiency and equilibrium. J. Optim. Theory Appl. 75, 221–264.
Luenberger, D.G., 1994a. Dual pareto efficiency. J. Econ. Theory 62, 70–85.
Luenberger, D.G., 1994b. Optimality and the theory of value. J. Econ. Theory 63, 147–169.
Luenberger, D.G., 1995a. Microeconomic Theory. McGraw-Hill, Boston.
Luenberger, D.G., 1995b. Externalities and benefits. J. Math. Econ. 24, 159–177.
Manello, A., 2017. Productivity growth, environmental regulation and win–win opportunities: the case of chemical industry in Italy and Germany. Eur. J. Oper. Res. 262 (2), 733–743.
Meyer, S.M., 1992. Environmentalism and Economic Prosperity: Testing the Environmental Impact Hypothesis. Project on Environmental Politics and Policy, Massachusetts Institute of Technology.
Meyer, S.M., 1996. Economic impact of environmental regulations. J.Environ.Law Pract. 4, 4–15.
Miao, Z., Baležentis, T., Tian, Z., Shao, S., Yong Geng, Y., Wu, R., 2019. Environmental performance and regulation effect of China's atmospheric pollution emissions: evidence from “three regions and ten urban agglomerations”. Environ. Resour. Econ. 74, 211–242. https://doi.org/10.1007/s10640-018-00315-6.
Mirza, F.M., Rizvi, S.B., Bergland, O., 2021. Service quality, technical efficiency and total factor productivity growth in Pakistan's post-reform electricity distribution companies. Util. Policy 68.
OECD Manual, 2001. Measuring productivity: measuring of aggregate and industrial-level productivity growth. Available at: https://www.oecd.org/sdd/productivity-stats/2352458.pdf.
Oh, D.H., 2010. A global Malmquist-Luenberger productivity index. J. Prod. Anal. 34 (3), 183–197.
Oh, D., Heshmati, A., 2010. A sequential Malmquist-Luenberger productivity index: environmentally sensitive productivity growth considering the progressive nature of technology. Energy Econ. 32 (6), 1345–1355.
Olley, S., Pakes, A., 1996. The dynamics of productivity in the telecommunications equipment industry. Econometrica 64, 1263–1295.
Pasurka, C.A., 2008. Perspectives on pollution abatement and competitiveness: theory, data, and analysis. Rev. Environ. Econ. Policy 2, 194–218.
Peng, X., 2020. Strategic interaction of environmental regulation and green productivity growth in China: green innovation or pollution refuge? Sci. Total Environ. 732, 139200.
Rehman, S.-U., Kraus, S., Shah, S.A., Khanin, D., Mahto, R.V., 2021. Analyzing the relationship between green innovation and environmental performance in large manufacturing firms. Technol. Forecast. Soc. Chang. 163, 120481.
Rehman, S.-U., Bresciani, S., Yahiaoui, D., Giacosa, E., 2022. Environmental sustainability orientation and corporate social responsibility influence on environmental performance of small and medium enterprises: the mediating effect of green capability. Corp. Soc. Responsib. Environ. Manag. 1–14. Special issue article.
Rostow, W.W., 1971. The Stages of Economic Growth. Cambridge University Press, Cambridge.
Rubashkina, Y., Galeotti, M., Verdolini, E., 2015. Environmental regulation and competitiveness: empirical evidence on the Porter hypothesis from European manufacturing sectors. Energy Policy 83, 288–300. https://doi.org/10.1016/j.enpol.2015.02.014.
Sakai, Si, Yano, J., Hirai, Y., et al., 2017. Waste prevention for sustainable resource and waste management. J.Mater.Cycles Waste Manag. 19, 1295–1313. https://doi.org/10.1007/s10163-017-0586-4.
Sarbu, M., 2017. Does social media increase labour productivity? J.Econ.Stat. 237 (2), 81–113.
Simar, L., Wilson, P., 1998. Sensitivity of efficiency scores, how to bootstrap in non-parametric frontier models. Manag.Sci. 44, 49–61.
Simar, L., Wilson, P., 1999. Estimating and bootstrapping Malmquist indices. Eur. J. Oper. Res. 115, 459–471.
Simar, L., Wilson, P., 2000a. A general methodology for bootstrapping in nonparametric frontier models. J. Appl. Stat. 27, 779–802.
Simar, L., Wilson, P., 2000b. Statistical inference in nonparametric frontier models: the state of the art. J. Prod. Anal. 13, 49–78.
Singh, S.K., Del Giudice, M., Chierici, R., Graziano, D., 2020. Green innovation and environmental performance: the role of green transformational leadership and green human resource management. Technol. Forecast. Soc. Chang. 150, 119762.
Silveira, N.J.C., Ferraz, D., Mello, D.S., Polloni-Silva, E., Moralles, H.F., Rebelatto, D.A. do N., 2021. Calculating models for total factor productivity measurement. Exacta. https://doi.org/10.5585/exactaep.2021.18140.
Song, Y., Wei, J., Zhu, J., Liu, J., Zhang, M., 2021. Environmental regulation, and economic growth: A new perspective based on technical level and healthy human capital. J. Clean. Prod. 318, 128520.

Sueyoshi, T., Goto, M., 2013. DEA environmental assessment in a time horizon: Malmquist index on fuel mix, electricity and CO2 of industrial nations. Energy Econ. 40, 370–382.
Sun, X., Ping, Z.-B., Dong, Z.-F., Chen, K.-L., Zhu, X.-D., Li, L.B., Tan, X.-Y., Zhu, B.-K., Liu, X., Zhou, C.-C., Fang, S., Xiong, W., 2021. Resources and environmental costs of China's rapid economic growth: from the latest theoretic SEEA framework to modeling practice. J. Clean. Prod. 315, 128126.
Tang, H.-I., Liu, J.-M., Wu, J.-G., 2020. The impact of command-and-control environmental regulation on enterprise total factor productivity: a quasi-natural experiment based on China's "two control zone" policy. J. Clean. Prod. 254, 120011.
Tsai, D.H., 2002. Environmental Policy and Technological Innovation: Evidence from Taiwan Manufacturing Industries. Conference paper. Presented at 5th Annual Conference on Global Economic Analysis, Taipei, Taiwan. Available at: https://www.gtap.agecon.purdue.edu/resources/res_display.asp?RecordID=1023.
Tzouvelekas, E., Vouvaki, D., Xepapadeas, A., 2007. Total Factor Productivity Growth and the Environment: A Case for Green Growth Accounting. The Fondazione Eni Enrico Mattei. Note di Lavoro Series Index. http://www.feem.it/Feem/Pub/Publications/WPapers/default.htm.
Wang, Y., Shen, N., 2016. Environmental regulation and environmental productivity: the case of China. Renew. Sust. Energ. Rev. 62, 758.
Wang, X., Shao, Q., 2019. Non-linear effects of heterogeneous environmental regulations on green growth in G20 countries: evidence from panel threshold regression. Sci. Total Environ. 660, 1346–1354.
Wang, X., Zhang, T., Nathwani, Y., Yang, F., Shao, Q., 2022. Environmental regulation, technology innovation, and low carbon development: revisiting the EKC Hypothesis, Porter Hypothesis, and Jevons'_Paradox in China's iron & steel industry. Technol. Forecast. Soc. Chang. 176, 121471.
Wang, Y., Sun, X., Guo, X., 2019. Environmental regulation and green productivity growth: empirical evidence on Porter Hypothesis from OECD industrial sectors. Energy Policy 132, 611–619.
Wei, W.W.L., Zhang, J.L., Wen, J.J., Wang, S., 2020. TFP growth in Chinese cities: the role of factor-intensity and industrial agglomeration. Econ. Model. 91, 534–549.
Wooldridge, J.M., 2009. On estimating firm-level production functions using proxy variables to control for unobservables. Econ. Lett. 104, 112–114.
Wu, Y., Wang, B., 2008. Environmental regulation and total factor productivity growth: an empirical study of the APEC economies. Econ. Res. J. 5, 19–33.
Wu, G., Baležentis, T., Sunc, C., Xuc, S., 2019. Source control or end-of-pipe control: mitigating air pollution at the regional level from the perspective of the total factor productivity change decomposition. Energy Policy 129, 1227–1239.
Yang, C.H., Tseng, Y.H., Chen, C.P., 2012. Environmental regulations, induced R&D, and productivity: evidence from Taiwan's manufacturing industries. Resour. Energy Econ. 34 (4), 514–532.
Yörük, B.K., Zaim, O., 2005. Productivity growth in OECD countries: a comparison with Malmquist indices. J. Comp. Econ. 33, 401–420.
Yu, M.M., Hsu, S.H., Chang, C.C., Lee, D.H., 2008. Productivity growth of Taiwan's major domestic airports in the presence of aircraft noise. Logist. Transp. Rev. 44, 543–554.
Yu, W., Ramanathan, R., Nath, P., 2017. Environmental pressures and performance: an analysis of the roles of environmental innovation strategy and marketing capability. Technol.Forecast.Soc.Change 117, 160–169.
Zhang, C., Liu, H., Bressers, H.T., Buchanan, K.S., 2011. Productivity growth and environmental regulations-accounting for undesirable outputs: analysis of China's thirty provincial regions using the Malmquist-Luenberger index. Ecol. Econ. 70 (12), 2369–2379.
Zhang, N., Jiang, F., 2019. The effect of environmental policy on Chinese firm's green productivity and shadow price: a meta frontier input distance function approach. Technol.Forecast.Soc.Change 144, 129–136.
Zhang, Y., Song, Y., Zou, H., 2020. Transformation of pollution control and green development: evidence from China's chemical industry. J. Environ. Manag. 275, 111246.
Zhou, P., Ang, B.W., Han, J.Y., 2010. Total factor carbon emission performance: a Malmquist index analysis. Energy Econ. 32 (1), 194–201.

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 modelling design. She has published on *European Journal of Social Science Education and Research* and *Economia Marche-Journal of Applied Economics*.

Carl Pasurka is an adjunct professor at the Schar School of Policy and Government, George Mason University. 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 and is currently an associate editor of Energy Economics. His current areas of research include 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.*

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*.