# Environmental Production and Productivity Growth: Evidence from European Paper and Pulp Manufacturing

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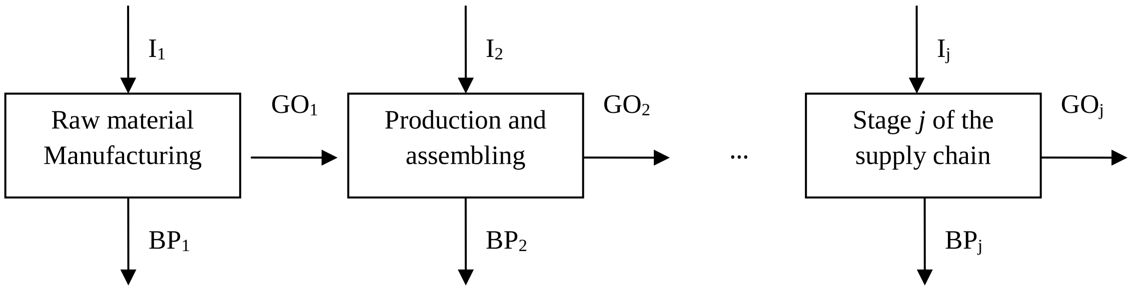
## Abstract

Production and manufacturing sector is one of the primary contributing factors to affect the environment which have been a very important topic studied in recent years. Many approaches are employed to reduce the impacts of production on the environment. More recently, carbon abatement technology and activities have been introduced in the production processes to reduce carbon emissions, as the implementation of emission trading programs in many industrial sectors, including the paper and pulp sector. Nevertheless, the costs of abatement activities will occur as a certain level of sacrifice in productivity growth, when the inputs are reallocated from good output production to the abatement activities in order to maintain the bad output under the regulated limit. However, it is still not clear that to what extent and how introduction of such technology will affect productivity. Therefore, it is worth investigating the opportunity cost of introducing such technology. In this paper, we offer new empirical evidence by studying panel data of 17 EU member states over the period 1995-2006. Productivity changes are calculated using data envelopment directional distance function with and without adapting the carbon abatement technology in the paper and pulp production. The results support our concern on the potential opportunity cost of introducing the carbon abatement technology, which leads to decline in productivity growth. In addition, the industrial production is not operating efficiently; on average it moves further away from the efficient production frontier over time.

**Keywords**: Green manufacturing, environmental management, productivity, data envelopment analysis.

## 1. Introduction

Environmental consciousness has emerged to be one of the most important topics in the last two decades (Chan et al., 2016). Various studies were conducted from a variety of perspectives. Production and manufacturing activities are notoriously considered as the major sources leading to various environmental impacts, which are challenges to many organisations (Beamon, 1999). This assertion is not surprising as a considerable amount of resources, particularly energy, is consumed during virtually all production processes and, as a consequence, a great amount of associated undesired secondary outputs have been produced that are normally not to be taken into consideration in the production and process stage. If this extends to the scope of the entire supply chain that involves the suppliers, manufacturers, distributors and so on, the accumulation of such undesired outputs (i.e. in some literature, called as bad outputs) could be enormous (Zhang et al., 1997). This can be demonstrated in Figure 1. In this connection, designing a green production process is definitely one of the vital concerns in the modern production engineering domain (Sundarakani et al., 2010).




$I_j$ = a set of Inputs at stage *j*
$GO_j$ = Good (i.e. desired) outputs of stage *j*
$BP_j$ = Bad outputs (e.g. $CO_2$ emission) of stage *j*

**Figure 1. A general inputs-outputs diagram of a supply chain**

Above also links to the concept of green production or green supply chain, the extended version of the former, which has been studied extensively. In 1990s, many studies were restricted to high level frameworks. For example, Lamming and Hampson (1996) attempted to link environment to a number of operations or supply chain issues such as quality management, lean production and so on. Walton et al. (1998) proposed a number of guidelines for supplier evaluation for integrating them into environmental management based on a number of cases study. The authors also further extended their findings to a number of driver actions for environmentally-friendly practices and illustrated them in the furniture industry (Handfield et al., 1998). As this strand of research evolved, a number of decision-making models were proposed to aid implementation of green practices. For instance, Clift and Wright (2000) developed an econometric model for analysing the relationship between the environmental impacts and economic value of mobile phones along its supply chain. They showed that the greatest environmental damage is associated with the primary resource industries and the results are disproportionate to the economic value generated along the supply chain. Sarkis (2003) made use of a hierarchical model to study the interdependence of different environmental factors on greens supply chain management. The model aims to assist decision-makers to find the best alternate supply chain strategies subject those factors. Kainuma and Tawara (2006) proposed a multiple attribute utility method for assessing a two-stage supply chain by taking reuse or recycling into consideration. Sundarakani et al. (2010)

utilised the long-range Lagrangian and the Eulerian transport methods to measure the carbon footprint of supply chains and highlight the importance of the design to reduce carbon emission. Their model considers the aggregate carbon emissions of various stages of a supply chain, which is similar to the concept proposed and analysed in this model. Wang et al. (2012) analysed a fashion supply chain by a fuzzy hierarchical model to access the risk of formulating different green initiatives. Their model can take uncertain parameters into account.

One way to mitigate the problem of producing undesired outputs is to employ carbon abatement technologies in the production process. Those technologies help alleviate carbon emissions and thus ease its impact on the environment, for example, in terms of global climate change. In other words, the carbon abatement technologies help reduce $BP_j$ in Figure 1. Chen and Xiang (2018) found that the efficiency of reducing carbon emissions of coal-fired power plants is highly characterised by the adoption of the most advanced abatement technologies. In a related study, Peng et al. (2018) concluded that in the China thermal power sector the potential to reduce carbon emissions using large-scale abatement technologies is huge, although this is varied in different provinces in China. Hsu and Lo (2017) investigated the potential of employing carbon abatement in the steel industry. They projected the cost of carbon abatement technology until 2030, and suggested that implementing the technology would be cost effective to reduce carbon emissions. In their study, however, they assumed that the carbon abatement technology will undergo steady growth and development in a long run. Reducing carbon emissions in light industry is also important. Zhang and Xie (2015) studied how carbon abatement technologies could help reduce carbon emissions in the electronic information industry. They claimed that the industry in China had not been practising in a sustainable way in terms of carbon emissions, but the trajectory is getting better over time since the 1980s. It is partly attributed to the government policies that required the implementation of carbon abatement technologies.

Above industrial examples demonstrate the need and motivation for studying the impact of environmental/green technology on productivity. The next question is thus how to achieve this objective. Investment for such technologies is substantial, and hence the effect of such implementation should be carefully considered. Obviously, there is always a mix of technologies or different level of reduction companies can utilise, but, unfortunately, it is still unclear that how such decision can be made. This is the major contribution of this research to help address this issue. This is further elaborated below.

When environmental concerns are taken into account in the design stage, discussion on Life-Cycle Assessment or Analysis (LCA) cannot be omitted. This is a scientific model to analyse the environmental impacts by taken the whole product life cycle, including material selection and production, manufacturing, usage, delivery, end-of-life treatment, and so on, into consideration (Hawkins et al., 2007; Yung et al., 2012). This is sometimes referred to as 'cradle to grave' or even 'cradle to cradle' analysis (Reap et al, 2008). Put it simple and with reference to Figure 1, LCA considers the aggregate inputs (materials, energy, and so on) and outputs (more specifically, secondary outputs or by-products which are related to environmental impacts) of various life cycle stages of a product. Conducting LCA can help designer to understand the environmental impacts of a design and hence alternatives can be pinpointed to the results for making improvement. Therefore, quantifying the aforementioned outputs and then converting them to measureable impact items for analysis can facilitate the decision-making process of a design. LCA can be employed in various applications. For example, electricity market (Stoppato, 2008), beer industry (Koroneos et al., 2005), building industry (Asif el al., 2007), offshore wind turbine plant (Weinzettel et al., 2009), among many others.

However, LCA is not without shortcomings. A survey indicated that 68% and 63% of the respondents considered that LCA is time-consuming and costly respectively (Cooper and Fava, 2008). In addition, accuracy of the data collection is also a barrier to successful LCA and thus some studies are conducted by taking this into account (e.g. Chan et al. 2013). Furthermore, LCA is case or company specific which means implications of previous studies may not be able to generalise to other cases. This can be reflected in an LCA study conducted by Lopes et al. (2003) for the paper pulp process (the target industry in this study). Their study is useful to compare two options (more specifically, two kinds of fuels) in terms of a number of environmental impacts. Having said that, such LCA cannot analyse the economic effect of introducing different technologies for the whole industry in general. Such decision is always necessary in the later stage of the analysis (Reich, 2005). This is also the major motivation to conduct this study in order to understand that the effect of introducing carbon abatement technologies at the industry level. The objective is to analyse how carbon abatement technologies can (or cannot) improve supply chain productivity or efficiency by both desirable and undesirable outputs in the production function, and hence opportunity cost into account.

In the literature, economic benefits from introducing pollution abatement technologies have not been clearly studied. Its investment does not appear to be economically viable under some conditions (Mo et al., 2018). Huang et al. (2015) investigated that the short-term and long-term optimal investment strategy based on cost-benefit analysis are different for the industry. It is obvious that employing pollution abatement technology or activities will not be costless. The good output production can be reduced due to the input reallocation from good output production to pollution abatement activities. In addition, this will require additional resources (including, for example, R&D investment in abatement technologies and management costs for the relevant processes), which can be considered as inputs, to organisations. This is particularly important when the undesired output is regulated to a certain up-limit (Aiken et al., 2009). In other words, more input is needed to maintain the same desirable output and suppress the undesirable output at the regulated level. Or, less desired output production is traded as the abatement costs. This sometimes implies a decline in traditional productivity (Färe et al., 2007a). In this connection, Färe et al. (2007b) compared the rate of technology change and productivity change of the U.S. 92 coal-fired electric power plants for 1985-1995. They modelled joint production of both desired and undesired outputs, which differs from the traditional productivity approach. Based on the panel data analysis, the authors concluded pollution abatement activities are associated with declines in traditional productivity and technical change, though the results were not statistically significant. Aiken et al. (2009) further studies the relationship between productivity and abatement activities for manufacturing industries in four countries, namely, Germany, Japan, the Netherlands and the United States, from 1987 to 2001. They analysed the production frontier of regulated and unregulated technology, and concluded that capital expenditures of the abatement technology are not linked to the decline in manufacturing productivity.

This paper contributes to the literature by offering new empirical evidence to the above debate, and by further scrutinizing the potential opportunity costs of abatement activities in the production process. We focus on the paper and pulp industry, which has been deemed as a high pollution generator (Thompson et al., 2001; Pokhrel and Viraraghavan, 2004; Zhu et al., 2005) and an energy intensive sector (Szabó et al., 2009). This industry has a long supply chain starting from forest harvesting and involves many organisations (Carlsson et al. 2009).

However, economic impact of this industry cannot be overlooked (Barla, 2007). In relation to our study, Hailu and Veeman (2000) employed a parametric distance function to analyse the desired outputs and by-products using the time series data for a single country's (i.e. the Canadian) paper and pulp industry. They found that the performance of the industry has been underestimated if pollutant outputs are ignored. They claimed that above findings was owing to the fact that the environmentally sensitive measure credits both desired outputs and its pollution abatement activities.

In this paper, we calculate productivity indices with and without taking environmental technology into account for paper and pulp production for EU27 countries over twelve years of 1995-2006. The comparison of those two sets of estimated productivity indices reveals insight to the opportunity costs of abatement technology/activities in the production process. Moreover, analysing this more recent available panel data allow us to provide a more comprehensive view on the impact of incorporating environmental technology in production on the industrial productivity change. Specifically, we follow Färe et al. (2009) approach and consider a decision making model for joint production of good and bad outputs. Data Envelopment Directional Distance Function Analysis is employed to calculate the productivity changes with and without adapting $CO_2$ emissions abatement technology in the paper and pulp production across EU27 member countries.

The empirical findings from this study confirm our concerns on the potential opportunity cost of environmental technology in the production process. To achieve green production, certain level of industrial productivity growth needs to be sacrificed. In general, over the twelve years of 1995-2005, pollution abatement technology/activities are associated with a slight decline the average annual productivity growth across our sample countries. In particular, in the countries where paper and pulp productions are ranked high, such as Finland, Italy and Estonia, the introduction of pollution abatement technology decreases on average, the productivity growth. Moreover, the efficiency change indices in those countries suggest that their good output production are on average further away from the efficient production frontier, when environmental technology is imposed. That means they generally have a reduced good output production at given inputs level, when abatement activities are considered in the paper and pulp production. In other words, more inputs are required to sustain the given good output production level. That appears to be consistent with the substantial increases in their technological changes over 1995-2006, as an implication of environmental technology development.

The remainder of this study is structured as follows. Section 2 presents the decision making model of joint production of good and bad outputs. Section 3 describes the data and empirical results. Section 4 provides a discussion on the implication of the finding and concludes the study.

## 2. Methodology

In this section, we first illustrate the decision making model as a joint production function through an environmental technology (i.e., CO2 emission abatement technology in this study). And then, we show the traditional approach (i.e., without incorporating abatement technology) derived from it. Finally, we introduce the pollution abatement index measure to bridge the estimated productivity indices by the two approaches. We start with formal theoretical production function, using the denotations consistent with those in the literature.

Let $x = (x_1, \ldots, x_N) \in \mathbb{R}_+^N$ denotes a vector of inputs, $y = (y_1, \ldots, y_M) \in \mathbb{R}_+^M$ denotes a vector of good (desired) outputs, and $b = (b_1, \ldots, b_I) \in \mathbb{R}_+^I$ denotes a vector of bad (undesired) outputs (by-products). Thus, the joint production function is specified as:

$$P(x) = \{(y, b): x \text{ can produce } (y, b)\}, x \in \mathbb{R}_+^N, \tag{1}$$

where the output set $P(x)$ represents the combinations of good and bad outputs $(y, b)$ that can be produced using the input vector $x$. $P(x)$ is a convex and compact set that satisfies the standard properties of no free lunch, possibility of inaction, and strong or free disposability of inputs.[1]

To assure the joint production of good and bad outputs through an environmental technology, two assumptions are further imposed, in addition to the usual strong disposability of good outputs.[2] They are,

i) if $(y, b) \in P(x)$ and $b = 0$ then $y = 0$;

ii) if $(y, b) \in P(x)$ and $0 \leq \theta \leq 1$ imply $(\theta y, \theta b) \in P(x)$.

The first assumption ensures the null-jointness of the output set.[3] That means no good output can be produced without producing any bad outputs. The second assumption ensures the jointly weak disposability of good and bad outputs.[4] This states that a reduction of the bad outputs is not costless, which may negatively influence the production level of the good outputs. In other words, abatement activities require resources that otherwise could have been used to expand the amount of the good outputs. Therefore, the joint production technology assumes, in principle, good outputs are economically disposable without any cost, but bad outputs are not when there are environmental regulations.

We next write the afore-defined joint production technology as a directional output distance function as defined by Chambers et al. (1996a, 1996b, 1998). Hence, we have,

$$\vec{D}_o(x, y, b; g_y, g_b) = \sup \{\theta: (y, b) + (\theta g_y, \theta g_b) \in P(x)\} \tag{2}$$

where $g = (g_y, g_b)$ and $\theta$, respectively, represent the direction and proportion in which the output vector $(y, b)$ is scaled to reach the boundary or frontier of the output set $P(x)$. The directional output distance function value $\theta$ is bounded between zero and one. A value equal to zero indicates the observed output vector is located on the frontier and, hence, being technically efficient; otherwise, technical inefficient.

In this study, we estimate the above defined directional output distance model under two situations: i) when abatement activities are incorporated in the production technology, i.e., $\vec{D}_o(x, y, b; y, 0)$, the directional vector is $g = (y, 0)$; and ii) when they are not, i.e., $\vec{D}_o(x, y, 0; y, 0)$, the bad outputs are excluded from the output set $P(x)$ and the directional vector is $g = (y, 0)$.[5] In the first situation (we call it Model 1 in the rest of this paper), given environmental regulations in which the bad outputs are limited to a certain level, some inputs are reallocated to abatement activities in the production process. For an output-orientated approach, that means for given input level, certain level of good output production is likely to be sacrificed to meet the regulated the bad outputs. In the second situation (we call it Model 2), there is no environmental regulation imposed on bad output production, and thus the bad

[1] see, Färe and Primont (1995) for discussions.

[2] The uausl strong disposability of good outputs condition: $(y, b) \in P(x)$ and $y' \leq y$ imply $(y', b) \in P(x)$. This condition implies that a reduction of the good outputs is feasible without a simultaneously reduction of the bad outputs.

[3] See, Shephard and Färe (1974).

[4] See, Shephard (1970).

[5] See Krautzberger and Wetzel (2012) for a similar approach.

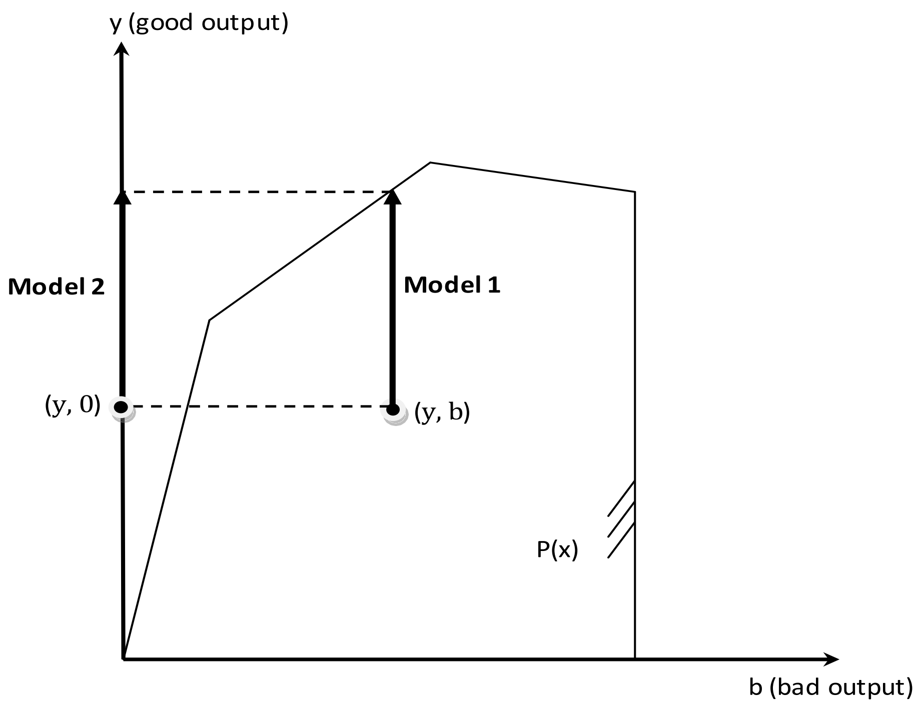
outputs are excluded from the output set. In other words, Model 2 is the traditional optimization approach to the sole good output production with all given inputs. Figure 2 illustrates the two directional output distance models.

To measure the model-specific productivity change, we use the sequential Malmquist (*SM*) productivity index as introduced by Oh and Heshmati (2010). Compared to the conventional Malmquist productivity index (Chung et. al 1997) that constructs the output set $P^t(x^t)$ in period $t$ from the observations in that period only, the *SM* index incorporates past information and includes all observations from period 1 up to period *t*. More formally, the sequential output set in period $t$ is defined as:

$$\bar{P}^t(x^t) = P^1(x^1) \cup P^2(x^2) \cup \dots \cup P^t(x^t) \qquad (3)$$

where $1 \leq t \leq T$. Hence, the SM index assumes that in each period of time all preceding technologies are also feasible and thus, in contrast to the conventional Malmquist index, eliminates the possibility of any technological regress by definition.[6] To calculate the *SM* index, we specify four directional distance functions for each of our two models as follows: $\vec{D}_o^t(x^t, y^t, b^t; g_y^t, g_b^t)$ ; $\vec{D}_o^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g_y^{t+1}, g_b^{t+1})$ ; $\vec{D}_o^t(x^{t+1}, y^{t+1}, b^{t+1}; g_y^{t+1}, g_b^{t+1})$ ; and $\vec{D}_o^{t+1}(x^t, y^t, b^t; g_y^t, g_b^t)$. The former two functions present that the sequential output set are from the same period; and the latter two indicate that the sequential output set are from different periods. Abbreviating the above functions with $\vec{D}_o^t(t)$ , $\vec{D}_o^{t+1}(t+1)$, $\vec{D}_o^t(t+1)$ and $\vec{D}_o^{t+1}(t)$, the *SM* index of productivity change between periods $t$ and $t+1$ can be defined as:

$$SM_t^{t+1} = \left[\frac{[1+\vec{D}_o^t(t)]}{[1+\vec{D}_o^t(t+1)]} \times \frac{[1+\vec{D}_o^{t+1}(t)]}{[1+\vec{D}_o^{t+1}(t+1)]}\right]^{\frac{1}{2}} \qquad (4)$$




[6] As noted by Shestalova (2003), technological regress can be reasonably explained for sectors like mining, whereas in most industrial sectors technology progresses or at least remains unchanged. In the paper and pulp manufacturing sector, we expect a technological progress in EU27 countries.

**Figure 2: Directional output distance models with and without environmental technology**

A value equals to unity indicates no productivity change. A value less than unity indicates productivity decrease and a value greater than unity indicates productivity increase. The *SM* index can be decomposed further into an efficiency change component $E_t^{t+1}$ and a technological change component $T_t^{t+1}$, that can be written as:

$$SM_t^{t+1} = E_t^{t+1} \times T_t^{t+1} \tag{5}$$

where,

$$E_t^{t+1} = \frac{\left[1+\vec{D}_o^t(t)\right]}{\left[1+\vec{D}_o^{t+1}(t+1)\right]} \tag{6}$$

and

$$T_t^{t+1} = \left[\frac{\left[1+\vec{D}_o^{t+1}(t)\right]}{\left[1+\vec{D}_o^t(t)\right]} \times \frac{\left[1+\vec{D}_o^{t+1}(t+1)\right]}{\left[1+\vec{D}_o^t(t+1)\right]}\right]^{\frac{1}{2}} \tag{7}$$

$E_t^{t+1}$ measures the change in output efficiency between two periods, which is the ratio of the distances of observations to their respective regulated frontiers, measured in terms of increased good output production while holding the bad output constant. If $E_t^{t+1} = 1$, the observation is the same from the frontier, i.e., no change in output efficiency between the two adjacent periods. If $E_t^{t+1} < 1$, the observation is further away from the frontier in the period *t+1*, and hence efficiency decrease. Finally, If $E_t^{t+1} > 1$, the observation is closer to the frontier over time, and thus efficiency increase. A shift of the production frontier between two adjacent periods *t* and *t+1* is measured by $T_t^{t+1}$. Frontier shifts towards increased good output production result in $T_t^{t+1} > 1$ , indicate technological progress. Otherwise, a value equal to unity indicates no shift in the frontier and hence no technological change over time.

The empirical estimation of productivity measure is normally implemented by either parametric or non-parametric method. The parametric approach, such as the stochastic frontier approach (SFA), specifies a functional form of the production technology and allows for random errors which follow a symmetric normal distribution while the output distance are measured by a truncated distribution. However, the parametric approach suffers from the problem of misspecification of the functional form. In theory, parametric estimators offer faster convergence and produce consistent estimates, but this would be true only if there is no misspecification of the functional form, which is particularly difficult to achieve in practice. In contrast, the nonparametric model, such as the Data Envelopment Analysis (DEA) which utilises linear programming method to construct an "envelope" of outputs against inputs usage, does not require the explicit specification of the form of the underlying production relationship (Zhang and Matthews, 2012; Arabi et al., 2017). The DEA method provides relative productivity measure that is units invariant, and therefore is also particular useful in estimating productivity with multiple input-output in measured in different units, such as the case in this paper.

Therefore, to operationalize Eq. (4), we follow Färe et al. (2001) using non-parametric DEA approach.. Let $\tau = 1, \dots, T$ time periods and $k = 1, \dots, K$ observations of inputs and outputs $(x^{k,\tau}, y^{k,\tau}, b^{k,\tau})$, we specify the sequential directional output distance function for each observation $k'$ at the time $t$ for Model 1 as the following linear program:

$$\begin{aligned} & \vec{D}_o^t\left(x^{t,k'}, y^{t,k'}, b^{t,k'}; y^{t,k'}, 0\right) = \max \theta \\ s.t. \quad & \textstyle\sum_{\tau=1}^{t} \sum_{k=1}^{K} z_k^\tau y_{km}^\tau \geq (1+\theta) y_{k'm}^t , \ m = 1, \dots, M \qquad \text{(i)} \\ & \textstyle\sum_{\tau=1}^{t} \sum_{k=1}^{K} z_k^\tau b_{ki}^\tau = b_{k'i}^t , \ i = 1, \dots, I \qquad \text{(ii)} \\ & \textstyle\sum_{\tau=1}^{t} \sum_{k=1}^{K} z_k^\tau x_{kn}^\tau \leq x_{k'n}^t , \ n = 1, \dots, N \qquad \text{(iii)} \end{aligned} \tag{8}$$

$z_k^\tau \geq 0\,,\; k = 1, \ldots, K$ (iv)

where $z_k^\tau$ are intensity variables assigning a weight to each observation $k$ when constructing the production frontier. The inequality constraints in (i) and (iii) state that observation $k'$ does not produce more good outputs or uses fewer inputs than its efficient benchmark on the frontier. That is, good outputs and inputs are freely disposable. Moreover, together with the inequality constraint in (i), the strict equality constraint in (ii) impose jointly weak disposability of good and bad outputs. Finally, the non-negativity constraint on the intensity variables in (iv) indicates that the production technology exhibits constant returns to scale (Chung et al., 1997). The solution to this program, the maximum value of $\theta$ for Model 1, shows that for given inputs, the extent of the good output production can be expanded relative to the efficient frontier while holding the bad outputs constant.

In order to ensure the above linear programme satisfies the null-jointness assumption, we add the following restrictions on the bad outputs:

$$\sum_{k=1}^{K} b_{ki}^{\tau} > 0, \quad i = 1, \ldots, I \; and \; \tau = 1, \ldots T \tag{9}$$

$$\sum_{i=1}^{I} b_{ki}^{\tau} > 0, \quad k = 1, \ldots, K \; and \; \tau = 1, \ldots T \tag{10}$$

The inequality constraint in (9) implies that each bad output is produced by at least one observation $k$, and the inequality constraint in (10) state that each observation $k$ produces at least one bad output. If for observation $k'$ all bad outputs are equal to zero $\left(b_{k'i}^{t} = 0, i = 1, \ldots, I\right)$, these restrictions imply that all intensity variables in (8) are zero ($z_k^\tau = 0, k = 1, \ldots, K$), which in turn implies that all good outputs must be zero $\left(y_{k'm}^{t} = 0, m = 1, \ldots, M\right)$. Hence, null-jointness is guaranteed (Färe et al. 2001). Finally, one can obtain the linear programs for the other three directional distance functions, $\vec{D}_o^t(t+1)$, $\vec{D}_o^{t+1}(t)$ and $\vec{D}_o^{t+1}(t+1)$ by substituting $t$ with $t+1$ only on the right hand side, only on the left hand side, and on both sides of the constraints in (i)-(iv), respectively.[7] Taking together, the four linear programmes represent Model 1 – the joint production technology through environmental regulations. By solving those linear programming problems for Model 1, we obtain environmental productivity change index (*SM<sub>G+D</sub>*). For Model 2 – without abatement technology in the production process, the equality constraint in (ii) and the restrictions (9) and (10) are dropped. Hence, the maximum value of $\theta$ for Model 2 shows that for given inputs, the extent of the good outputs can be expanded relative to the efficient frontier with completely ignoring bad outputs.[8] Similarly, by solving linear programming problems for Model 2, we obtain the second set of traditional productivity change index ($SM_G$).

Finally, we measure the pollution abatement index (PAI) as the ratio of $SM_G$ to $SM_{G+D}$, as similarly defined by Aiken et al. (2009), That is,

$$\text{PAI} = \frac{SM_G}{SM_{G+D}} \tag{11}$$

This index provides an understanding about the opportunity costs of abatement activities and its impact on productivity under environmental regulations. If the good output production associated with the traditional and joint (environmental) production frontiers changes by the same percentage, PAI = 1 and the introduction of abatement activities in the production process has no effect on productivity. If PAI > 1, meaning that the good output production

[7] Note that if the observed data for observation $k'$ in period $t+1$ is located above the frontier in period $t$ the linear program for the mixed period directional distance function $\vec{D}_o^t(t+1)$ yields an infeasible solution.

[8] Note that the derectional distance function for Model 2 is $\vec{D}_o^t\left(x^{t,k'}, y^{t,k'}, 0; y^{t,k'}, 0\right) = \max\theta$ in which the bad outputs are excluded. That means the linear programming is to optimize solely the good outputs, for given inputs.

associated with the traditional increases by a larger percentage than its production associated with the joint (environmental) production frontiers, the abatement activities is associated with reduced productivity growth. Finally, if PAI < 1, meaning that the good output production associated with the traditional increases by a smaller percentage than its production associated with the joint (environmental) production frontiers, the abatement activities is associated with increased productivity growth.

## 3. Data and empirical results

We collect, according to the International Standard Industrial Classification (ISIC), the industrial level production data under the industry categories C21 for the Paper and Pulp sector for EU27 countries. Due to missing data problems, the final panel dataset for our productivity analysis contains aggregated industrial production information for seventeen countries, over the time period 1995-2006.[9] Table 1 lists the countries studied and their observation years.

**Table 1: Countries and their observation years**

| Country code | Country name | Years observed |
|---|---|---|
| AT | Austria | 1995-2006 |
| BE | Belgium | 1995-2006 |
| CZ | Czech Republic | 1995-2006 |
| DE | Germany | 1995-2006 |
| DK | Denmark | 1995-2006 |
| ES | Spain | 1995-2006 |
| FI | Finland | 1996-2005 |
| FR | France | 1995-2006 |
| GR | Greece | 1995-2006 |
| HU | Hungary | 1995-2006 |
| IT | Italy | 1995-2006 |
| NL | Netherlands | 1995-2006 |
| PL | Poland | 1995-2006 |
| SE | Sweden | 1995-2006 |
| SK | Slovak Republic | 1996-2006 |
| SL | Slovenia | 1996-2004, 2005-2006 |
| UK | United Kingdom | 1995-2006 |

The raw production information, used to measure our input and output variables in the productivity analysis, are exacted from the OECD Structural Analysis (STAN) Database for industrial analysis (OECD 2011a). They are measured in local currency units at current prices, except employees which are measured in numbers. GDP deflators from the OECD (OECD 2011b) are used to transform those series into constant prices based on the year 2000.[10] For cross-country comparisons, the local currency measures are converted to an international common unit using purchasing power parities (PPPs) collected from the OECD (OECD 2011b). Our input variables are *intermediate inputs* (incl. energy, materials and services),

[9] Switzerland and the nine other member states of the European Union could not be included in the analysis because of missing data.

[10] GDP deflators are used due to incomplete industry-specific deflators in the OECD Structural Analysis database.

*capital stock* and *number of employees*. *Gross output* is considered as the good (desired) output and *$CO_2$ emissions* as the bad (undesired) output.[11]

To calculate the capital stock, we employ the standard perpetual inventory method (PIM) specified as follows:

$$K_{i,t} = (1-\delta)K_{i,t-1} + I_{i,t} \quad (12)$$

where $K_{i,t}$ and $I_{i,t}$ are the capital stock and the gross fixed capital formation in the paper and pulp sector of country $i$ in period $t$, respectively; and $\delta$ is a uniform depreciation rate assumed to be 5% per year.[12] The initial capital stock $K_0$ for each country is calculated as $I_0/(g_I + \delta)$, where $I_0$ is the country's value of gross fixed capital formation in the paper and pulp sector in 1995, $g_I$ is the country's average annual growth rate of gross fixed capital formation between 1995 and 2006 (European Communities, 2007), and $\delta$ again represents depreciation of 5%.

Our bad output measure, $CO_2$ emissions (measured in thousands of tons), are extracted from Eurostat's Air Emissions Accounts (AEA), which report air emissions by the economic activities from which the emissions are originated (Eurostat 2011). The production and consumption activities are classified according to the Statistical Classification of Economic Activities in the European Community (NACE).[13] This classification is compatible with the ISIC used in the STAN Database and hence allows us to combine $CO_2$ emissions from economic activities with economic figures on an industrial level. Table 2 presents a statistical summary of inputs and outputs variables used in this study.

**Table 2: Statistical summary of variables**

| Variable | Unit | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Capital Stock | million int. US$ | 2,970 | 3,290 | 4.75 | 15,400 |
| Labors | number in thousands | 42,882 | 40,343 | 5,252 | 166,000 |
| Intermediates | million int. US$ | 6,460 | 5,840 | 552 | 26,200 |
| Gross Output | million int. US$ | 8,339 | 8,530 | 751 | 37,800 |
| $CO_2$ Emission | tons in thousands | 2,202 | 2,059 | 175 | 7,127 |

Table 3 reports the average good and bad outputs and $CO_2$ intensity across our sample countries over the twelve observations years. The $CO_2$ intensity is calculated as the ratio of $CO_2$ emission to gross output (good) production. The high production of good output is generally associated with high level of pollution (i.e., the $CO_2$ emissions). This can be seen from the top paper and pulp producer as DE, ES, FI, IT, SE and UK (which are highlighted in Table 3), whose gross outputs range from above 11,000 to over 30,000 million US$s, accompanied with high $CO_2$ emissions ranging from 2270 to 6549 thousand tons on average. However, a low good output production does not always indicate a proportionately low CO2 emission. This can be seen from the high CO2 intensities of 0.58 and 0.44 in SI and SK, respectively, with very low paper production at 891 and 1993 million US$s. The above observations fall into the line of the jointly weak disposability of good and bad outputs in the production.

[11] This variable choice follows the gross output concept of productivity measurement appropriate when analysing firm or industry level data. For a detailed comparison of gross output based and value added based productivity measures see the "OECD Manual on Measuring Productivity" (OECD 2001).

[12] The 5% depreciation rate is a country average derived from diverse sources such as Abadir (2001) and Görzig (2007). Testing the robustness of our estimations we also applied a 3% and 10% depreciation rate. The results reveal no significant differences. The information on the gross fixed capital formation was drawn from the STAN.

[13] NACE stands for 'Nomenclature statistique des activités économiques dans la Communauté européenne'.

**Table 3: Average good and bad outputs and $CO_2$ intensity across countries, 1995-2006**

| Country | $CO_2$ Emission (in ,000 tons) | Gross Output (in mln US$s) | $CO_2$ Intensity |
|---|---|---|---|
| | | Mean | |
| AT | 964 | 5275 | 0.18 |
| BE | 712 | 3969 | 0.18 |
| CZ | 523 | 3321 | 0.16 |
| DE | 6549 | 30610 | 0.21 |
| DK | 209 | 1195 | 0.17 |
| ES | 2772 | 12680 | 0.22 |
| FI | 4125 | 13700 | 0.30 |
| GR | 285 | 1635 | 0.17 |
| HU | 199 | 1774 | 0.11 |
| IT | 4981 | 21010 | 0.24 |
| NL | 1337 | 5616 | 0.24 |
| NO | 543 | 2263 | 0.24 |
| PL | 1301 | 6367 | 0.20 |
| SE | 2270 | 11040 | 0.21 |
| SI | 516 | 891 | 0.58 |
| SK | 878 | 1993 | 0.44 |
| UK | 4190 | 18420 | 0.23 |
| Mean | 1903 | 8339 | 0.24 |
| Obs. | 204 | 204 | 204 |

Table 4 describes the average annual changes in inputs and outputs over 1995-2006. The negative growth of CO2 intensity indicates that the increase (decrease) in good output growth is greater (less) than that in CO2 emission growth over time. This implies environmental improvements in the paper and pulp production. However, this relates nothing to the productivity change, which requires looking further at the changes in the inputs. It can be seen from Table 4, there are significant increases in capital and intermediate inputs in the production in most of our sample countries. This appears somehow reflecting the introduction of environmental technology in the production.

Our empirical results of traditional and environmental productivity changes, the efficiency change and technological change components, and the pollution abatement index are reported in Tables 5 and 6.[14] In general, the empirical findings confirm our concerns on the potential opportunity cost of environmental technology (i.e. pollution abatement activities) in the paper and pulp production process. A certain level of industrial productivity growth needs to be sacrificed to achieve green production. Over the twelve observation years of 1995-2006, the pollution abatement technology/activities are associated with a slight decline in the average annual productivity growth across our sample countries. In particular, in the countries where paper and pulp productions are ranked high, such as Finland, Italy and Estonia, the introduction of pollution abatement technology decreases the productivity growth. Moreover, the efficiency change indices in those countries suggest that their good output production are on average further away from the efficient production frontier, when environmental technology is imposed. That means they generally have a reduced good output production at given inputs level, when abatement activities are considered in their paper and pulp production. This appears to be explained by the inputs reallocation from good output production to abatement activities. In other words, more inputs are required to sustain the given good output production level. This appears to be consistent with the substantial

[14] All reported indices are geometric means. Refer to methodology section for economic interpretation.

increases in their technological change over 1995-2006, which can be seen as the implication of environmental technology development. Below, we first discuss the results in Table 5 in detail, followed by the results in Table 6 in the similar pattern.

**Table 4: Average annual growth rate (in %) over 12 years over 1995-2006 across countries**

| Country | Gross Output | CO2 Emission | Capital Stock | Labor | Intermediates. | CO2 intensity |
|---|---|---|---|---|---|---|
| AT | 6.52 | 2.09 | 4.81 | -0.57 | 7.43 | -3.06 |
| BE | 5.26 | -0.47 | 0.15 | -2.59 | 6.35 | -2.53 |
| CZ | 1.58 | 2.07 | 9.63 | -3.79 | 2.52 | 2.41 |
| DE | 7.44 | 0.99 | 4.49 | -0.58 | 8.32 | -5.28 |
| DK | 2.59 | 1.16 | 3.91 | -2.55 | 3.48 | 0.67 |
| ES | 4.13 | 1.99 | 5.38 | 1.93 | 5.19 | -0.75 |
| FI | 7.09 | 0.95 | 12.93 | -1.00 | 7.97 | -4.08 |
| GR | 0.83 | 0.28 | 36.12 | -2.18 | 0.73 | 2.91 |
| HU | -1.85 | 1.18 | 10.04 | 2.66 | -0.76 | 4.33 |
| IT | 2.27 | -0.48 | 3.89 | -0.16 | 3.77 | -1.22 |
| LU | 4.15 | -4.01 | 9.25 | -3.14 | 4.91 | -6.62 |
| NL | 4.95 | 1.72 | 10.34 | -0.47 | 5.72 | -1.56 |
| NO | -0.88 | 0.24 | -3.72 | -2.69 | -0.82 | 1.96 |
| PL | 2.01 | -2.42 | -0.02 | -4.67 | 2.20 | -1.78 |
| PT | 11.87 | 1.12 | 16.66 | -2.88 | 11.51 | -5.36 |
| SE | 5.56 | 0.34 | 44.86 | -1.54 | 7.44 | -3.38 |
| SI | 0.55 | -2.04 | 63.44 | -2.11 | 0.34 | -1.08 |
| SK | 5.11 | -2.18 | 48.88 | -0.27 | 5.98 | -4.11 |
| UK | 0.29 | -0.13 | -4.26 | -1.56 | 1.40 | 0.44 |
| Mean | 3.42 | 0.32 | 14.82 | -1.34 | 4.24 | -1.14 |

In Table 5, we present the estimated results as geometric mean average over 1995-2006 by country. The first three columns report geometric means of productivity change, efficiency change and technological change under traditional production technology (i.e., without abatement activities in the production process). They are followed by the same indices, in the same sequence, under the joint production technology through environmental regulations (i.e., incorporating abatement activities in the production process). Finally, the pollution abatement index is reported in the last column. Six out of seventeen countries in our sample (they are BE, CZ, ES, FI, IT and SK) show abatement activities are associated with declines in the environment productivity growth, with their PAIs above unity. Among those, only BE and FI show increases in their environmental productivities, with average annual growth rates of 2.9% and 6.1%, respectively. Though, their good output productions are further away from efficient environmental production frontier over time, with average annual decreases of 2.8% and 7.6% in their output efficiencies. In the eleven other countries, only three countries have positive growth in their environment productivities, with average annual increases of 2.3% in DE, 4.9% in SE and 11.4% in AT, over 1995-2006. In addition, almost all countries, but DE and SE, exhibit declines in output efficiencies, range from average annual decreases of 17.3% in ES to 0.4% in AT. In contrast, all the sample countries show significant technological progress under environmental production technology, with average annual increases in technical change range from 0.6% to 15%.

**Table 5: Geometric mean of productivity changes over 1995-2006 across countries**

| | Traditional technology | | | Environmental technology | | | |
|---|---|---|---|---|---|---|---|
| **Country** | **$SM_G$** | **$E_G$** | **$T_G$** | **$SM_{G+B}$** | **$E_{G+B}$** | **$T_{G+B}$** | **PAI** |
| **AT** | 1.1026 | 1.0007 | 1.1017 | 1.1137 | 0.9961 | 1.1179 | 0.9901 |
| **BE** | 1.0329 | 0.9986 | 1.0344 | 1.0288 | 0.9717 | 1.0588 | 1.0040 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **CZ** | 0.9257 | 0.9257 | 1.0000 | 0.9166 | 0.8910 | 1.0288 | 1.0099 |
| **DE** | 0.9667 | 0.9667 | 1.0000 | 1.0230 | 1.0055 | 1.0175 | 0.9450 |
| **DK** | 0.8905 | 0.8905 | 1.0000 | 0.9301 | 0.8915 | 1.0432 | 0.9574 |
| **ES** | 0.9026 | 0.8776 | 1.0284 | 0.8664 | 0.8273 | 1.0473 | 1.0418 |
| **FI** | 1.1871 | 1.0000 | 1.1872 | 1.0614 | 0.9232 | 1.1497 | 1.1184 |
| **FR** | 0.9036 | 0.8794 | 1.0276 | 0.9303 | 0.8924 | 1.0425 | 0.9713 |
| **GR** | 0.8748 | 0.8748 | 1.0000 | 0.8946 | 0.8763 | 1.0209 | 0.9779 |
| **HU** | 0.7583 | 0.7583 | 1.0000 | 0.8779 | 0.8722 | 1.0065 | 0.8637 |
| **IT** | 0.9177 | 0.8706 | 1.0540 | 0.9107 | 0.8316 | 1.0952 | 1.0077 |
| **NL** | 0.9434 | 0.9318 | 1.0123 | 0.9531 | 0.9298 | 1.0251 | 0.9897 |
| **PL** | 0.8057 | 0.8057 | 1.0000 | 0.9085 | 0.8919 | 1.0185 | 0.8868 |
| **SE** | 0.8912 | 0.8705 | 1.0238 | 1.0489 | 1.0001 | 1.0489 | 0.8496 |
| **SK** | 0.8475 | 0.8475 | 1.0000 | 0.8442 | 0.8416 | 1.0030 | 1.0039 |
| **SL** | 0.7681 | 0.7681 | 1.0000 | 0.8359 | 0.8321 | 1.0045 | 0.9189 |
| **UK** | 0.8906 | 0.8906 | 1.0000 | 0.9054 | 0.8894 | 1.0179 | 0.9837 |

The results reported in Table 6 show the similar pattern with that in Table 5, but by observation years. It can be seen for Table 6, the paper and pulp sectors from the 17 EU countries experienced slight decline in the environmental productivity growth over the twelve years from 1995 to 2006, with the PAI equal to 1.0089, slightly greater than unity. And again, there is an overall 3% progress in technology in the environmental production across all countries over 1995-2006, despite a further 0.9% annual decrease in productivity when incorporating abatement activities in the production process.

**Table 6: Geometric mean of productivity changes for each two-year period over 1995-2006**

| | **Traditional technology** | | | **Environmental technology** | | | **PAI** |
|---|---|---|---|---|---|---|---|
| | SM_G | E_G | T_G | SM_GB | E_GB | T_GB | |
| 95-96 | 0.9135 | 0.9135 | 1.0000 | 0.8898 | 0.9525 | 1.0009 | 1.0265 |
| 96-97 | 1.0049 | 1.0049 | 1.0000 | 0.9789 | 0.9732 | 1.0067 | 1.0265 |
| 97-98 | 1.0039 | 1.0039 | 1.0000 | 1.0073 | 1.0060 | 1.0080 | 0.9966 |
| 98-99 | 1.0019 | 1.0003 | 1.0016 | 1.0154 | 1.0110 | 1.0123 | 0.9868 |
| 99-00 | 1.0050 | 0.9929 | 1.0121 | 1.0096 | 0.9855 | 1.0370 | 0.9954 |
| 00-01 | 1.0158 | 1.0092 | 1.0066 | 1.0049 | 0.9985 | 1.0437 | 1.0108 |
| 01-02 | 0.9948 | 0.9948 | 1.0000 | 0.9945 | 0.9945 | 1.0437 | 1.0004 |
| 02-03 | 0.9823 | 0.9823 | 1.0000 | 0.9839 | 0.9839 | 1.0437 | 0.9984 |
| 03-04 | 0.9966 | 0.9966 | 1.0000 | 1.0023 | 1.0023 | 1.0437 | 0.9944 |
| 04-05 | 0.9862 | 0.9862 | 1.0000 | 0.9228 | 0.9805 | 1.0437 | 1.0686 |
| 05-06 | 1.0092 | 1.0054 | 1.0034 | 1.0081 | 1.0081 | 1.0438 | 1.0010 |
| 1995-2006 | 0.9922 | 0.9900 | 1.0022 | 0.9834 | 0.9905 | 1.0296 | 1.0089 |

## 4. Conclusions

The study provides empirical evidence to support the assertion that introducing carbon abatement technology will lead to decline in productivity. The model allows the analysis of joint production of good and bad outputs through environmental regulations. Based on the measurement of the PAI index on panel data of 17 EU countries from 1995-2006 in the paper and pulp industry, it has been confirmed that the opportunity costs of carbon abatement activities exist, which means that productivity (or to be precise, environmental productivity) and hence productivity growth needs to be sacrificed. In other words, the costs of these abatement activities are actually paid off by reduction in production output efficiency. Since the main source of resources used in manufacturing processes is energy, such inefficiency will be highly likely to affect the energy efficiency which will then generate proportionately higher carbon emission for given good output level in principle. In order to reduce the unexpectedly high emission, this phenomenon repeats indefinitely which will undermine the anticipated benefits from the carbon abatement activities in the longer term. This gives rise to serious implications to many industries before incorporating the abatement technology and activities in the production processes. Therefore, the industry should not simply reduce the bad output by sacrificing the good output. Although protecting the environment is important, reducing the level of bad output should have been done efficiently so as to sustain the productivity and economic growth. This is analogue to the scenario that we can always reduce the amount of bad output by reducing the level of good output without doing anything.

The results of this paper are intuitive to policy makers and practitioners: the optimal policy should take the total costs and total economic benefits into account, rather than impose regulated bad output limits through legislation, for example. On the one hand, introducing carbon abatement technologies can help reduce carbon emissions and thus help tackle environmental issues by reducing carbon emissions. On the other hand, that will, generally speaking, come along with a price (the opportunity cost) because the productivity growth decreases as a consequence. This supports Hsu and Lo (2017)'s findings. This study also help explain why Peng et al. (2018) found that using carbon abatement technologies is beneficial more to heavy industries. It is because the associated opportunity cost is lower, in term of percentage to the overall cost. This compromise can be leveraged by subsidising the usage of this carbon abatement technologies by, for example, introducing tax exemption. This reduction in tax income is indirectly funded by the reduction in social cost due to reduction in carbon emissions (i.e., pollution). In a long run, policy makers can promote research and development on the carbon abatement technology so that the associated opportunity cost will be mitigated.

One limitation of this study is that only single industry has been studied. Although the chosen industry is a typical manufacturing industry that is similar to many other manufacturing industries, future research can be extended to other industries in order to better generalise the results. For example, the authors are now collecting data in other energy intensive manufacturing industries. Another limitation of this study is that data are collected from EU countries, which means they are developed countries. The authors acknowledge that the characteristics between developed countries and developing countries may be different in the context of this study. In this connection, a comparison between developed and developing economies can be undertaken in order to see if there is any difference through countries' political and economic idiosyncrasies.

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