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Characterizing the Difference between Indirect and Direct CO₂ Emissions: Evidence from Korean Manufacturing Industries, 2004–2010

Sinwoo Lee ¹, Dong-Woon Noh ² and Dong-hyun Oh ^{1,*}

¹ Department of Industrial Engineering and Management, Inha University, 100 Inha-ro, Nam-gu, Incheon 22212, Korea; lsw3478@inha.edu

² Korea Energy Economics Institute, 405-11 Jongga-ro, Jung-gu, Ulsan 44543, Korea; dwroh@keei.re.kr

* Correspondence: donghyun.oh@inha.ac.kr; Tel.: +82-32-860-7372; Fax: +82-32-867-7360

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Abstract: This study measures and decomposes green productivity growth of Korean manufacturing industries between 2004 and 2010 using the Malmquist-Luenberger productivity index. We focus on differences in the measures of productivity growth by distinguishing carbon emissions from either end-user industries or the electricity generation industry. Empirical results suggest three main findings. First, the efficiency of total emissions is higher than that of direct emissions except for the shipbuilding industry. Second, green productivity in the manufacturing sector increased during the study period. Finally, green productivity depends on the indirect emissions of each industry. These results indicate that policymakers need to deliberately develop policy tools for mitigating carbon emissions of the manufacturing industrial sectors based on our empirical findings.

Keywords: green productivity; Malmquist-Luenberger productivity index; greenhouse gas emissions; total emissions; direct emissions; indirect emissions

1. Introduction

Greenhouse gas emissions have been one of the global environmental concerns [1]. The international community is faced with the threat of climate change mainly because of the increase in greenhouse gas emissions such as CO₂. To mitigate this problem, many countries have attempted to reduce greenhouse gases under the United Nations Framework Convention on Climate Change. Under the Kyoto Protocol, Korea made voluntary efforts to reduce greenhouse gas emissions by 30% by 2020 relative to the projected business-as-usual (BAU) level. The priority for this plan is to establish measures for low carbon green growth at the industry level while fostering economic growth. In the meantime, a new climate change agreement, the Paris Agreement, has been adopted to bind several countries that were previously excluded from the responsibilities under the Kyoto Protocol. By doing so, Korea has agreed to reduce greenhouse gases emissions by 37% compared to forecasted values by 2030. These efforts made it possible for Korea to reduce CO₂ emissions from 630 MT CO₂ in 2013 to 610 Mt CO₂ in 2014 [2].

In 2008, Korea introduced a policy for low carbon green growth in order to simultaneously foster economic growth and reduce environmental degradation. This policy was set as a national development paradigm in line with coping with the global environmental and energy crisis in 2008. For this, the Korean government emphasized green growth strategy and policy. International organizations such as the OECD, the World Bank and UNEP evaluated Korea's green growth policy as a new economic growth paradigm that could overcome the global ecosystem crisis of the 21st century and preserve human civilization. The emission trading scheme (ETS) was also

launched in 2015 to enable the market mechanism to mitigate carbon emissions [3]. (The operation on ETS is based on the Coase theorem that the bargaining makes it possible to allocate outcome efficiently regardless of the initial assignment of property rights [4]).

Despite the abovementioned efforts on mitigating greenhouse gas emissions, a consensus on handling the cost of carbon emissions has not been made, especially for the direct versus indirect gas emissions. The greenhouse gas emissions in production activities are classified into the direct emissions of Scope I and indirect emissions of Scope II. If the direct emissions of Scope I is adapted, the operators of the sources of these emissions are obligated to incur costs associated with greenhouse gas emissions. For example, this includes emissions from combustion in owned or controlled boilers, furnaces, vehicles, as well as emissions from chemical production in owned or controlled process equipment. The indirect emissions of scope II are highly related with intermediate users and end users outside the electrical, thermal, and other energy uses related to greenhouse gas emissions; and they are responsible for the cost incurred in mitigating CO₂ emissions. This scheme is believed to manage greenhouse gas emissions effectively [5].

The above scheme, Scope I and Scope II, is considered when developing environment-related policies for most countries. However, to some extent, Korea's scheme is different from other countries' approaches. For example, Korea regulates the indirect emissions from the electricity consumption side, while the EU only considers the direct emissions. The difference between these schemes leads to double counting in estimating emissions since electricity generating and consuming activities simultaneously require emission allowances [6]. Nevertheless, the Korean government has preferred the indirect emission for the following reasons: (i) To reduce the electric intensity of the economy; (ii) to include carbon prices on the consumption side; and (iii) to evenly distribute the emission reduction burden across industrial sectors [6].

Although Korea has attempted to mitigate greenhouse gas emissions and sustain economic growth, green productivity of Korea remains below that of OECD countries [7–9]. Furthermore, the green productivity of the highly emitting sectors has not yet been identified. Also, unlike in Europe, Korea's emission scheme is applied differently across industries, so they are likely to be misleadingly estimated when evaluating the efficiency and productivity of the industry.

This aims at diagnosing the status quo of the Korean emission scheme by employing the Malmquist-Luenberger index (ML index hereafter). The reason for using the ML index is that it yields green productivity growth as well as its decomposed factors. To investigate the effect of indirect emissions, green productivity growth of total emissions and direct emissions are compared. Empirical analyses were conducted using a data set for 17 manufacturing industrial sectors in Korea from 2004 to 2010. The empirical findings are believed to help policymakers prepare policy tools for mitigating greenhouse gas emissions and sustaining economic growth. As far as the authors know, this study is the first attempt that distinguishes total emissions and direct emissions in measuring green productivity growth.

The remaining sections of this paper are organized as follows: Section 2 presents the literature review on mitigation of greenhouse gas emissions, especially focusing on studies employing the ML index approaches. A methodological discussion is provided in Section 3. Section 4 discusses the data set, and empirical results are discussed in Section 5. Section 6 briefly provides a conclusion and policy implications.

2. Literature Review

The concept of the ML index is introduced by Chung et al [10]. The main purpose of the ML index is to measure productivity growth of an economic agent by investigating the reduction of undesirable outputs and the production of desirable outputs. The sector-level studies of green productivity include Chung et al., Piot-Lepetit and Le Moing, Yu et al., He et al., Chung and Heshmati, Emrouznejad and Yang and Fan et al [10–16].

Chung et al. [10] provides a detailed methodological aspect of the ML index. Using the linear programming technique, they measure the green productivity growth index and its decomposed factors for the Swedish paper and pulp mills during the period of 1986–1990. They emphasize that the ML index does not require any information on input and output prices, which is regarded as the main virtue of using the ML index. Also, they compared the traditional Malmquist index and the ML index.

Piot-Lepetit and Le Moing [11] measure the change in green productivity of the French pig sector to examine the relationship between environmental regulations and green productivity between 1996 and 2001. Their aim is to consider the efficiency of the European regulations on water pollution derived from nitrates in agriculture. They find that the productivity of the French pig sector increased mainly due to the efficiency increase rather than the technological progress, and argue that a win-win effect can be derived between the efficiency gain and the environmental regulation. Yu et al. [12] measured the green productivity of the Taiwanese airports from 1993 to 1999, and found green productivity of these airports increased during the study period. He et al. [13] measured energy efficiency and the changes in green productivity of China's iron and steel industry from 2001 to 2008. Empirical results indicate that the average energy efficiency was 61.1% for the period of 2001–2008. Technical change was the main contributor to the productivity growth during this period. They also argue that the productivity growth of China's iron and steel industry is highly likely to be underestimated if the effect of undesirable outputs is ignored. Chung and Heshmati [14] measured productivity growth at the industry level and decomposed the green productivity index to obtain in-depth information on the green growth. They used 14 Korean industrial sectorial data from 1981 to 2010 for this purpose. Emrouznejad and Yang [15] provide a framework for measuring eco-efficiency with CO₂ emissions in Chinese manufacturing industries. They found that the environmental regulation pushes the technological frontier in the direction of more desirable outputs and less undesirable outputs. This implies that the regulation helps to mitigate CO₂ emissions and sustain the economic growth, and it leads to technological progress. Fan et al. [16] analyzed and decomposed the total CO₂ emission performance of 32 industrial sectors in Shanghai from 1994 to 2011. They found that the environmentally sensitive productivity of the entire industry in Shanghai has kept improving in recent years. The technical progress is the main contributor in ameliorating environmental productivity.

Also, state-level studies employing the ML index are abundant. Färe et al. [17] measured green productivity in the manufacturing sectors of 48 states in the United States from 1974 to 1986. Jeon and Sickles [18] measured green productivity and general productivity in Asian and OECD countries, and they found that (i) technical change was the main source of productivity growth and (ii) less-developed Asian countries showed relative low green productivity growth. Yörük and Zaum [19] compared the Malmquist index (M index hereafter) and ML index for the OECD member countries, and argue that the ML index is more practical than the M index since the former considers undesirable outputs in measuring productivity growth. Kumar [20] applied the ML index to analyze the environmentally sensitive productivity growth of 41 countries from 1971 to 1992, and found that technical change is the main contributor to productivity growth and that the productivity growth of Annex I countries is higher than that of non-Annex I countries. Bing et al. [21], using the ML index, analyzed the impact of environmental regulations for 17 APEC countries from 1980 to 2004. Aparicio et al. [22] analyzed the productivity growth for 39 countries from 1995 to 2007. They show that the environmental productivity stagnation prevails across countries, and technological progress is the main contributor to the productivity growth. However, the productivity growth is offset by efficiency deterioration. Scotti and Volta [23] measured the CO₂ emissions of European airlines for the period of 2000–2010. They computed airlines' productivity with an environmentally sensitive productivity growth index, and they found that the airlines experienced low environmental productivity growth. Zhang et al. [24] employed the ML productivity index to evaluate China's growth in total factor productivity, incorporating undesirable outputs, during the period from 1989 to 2008.

The methodological advancements in the ML index can be found in several studies such as Oh and Heshmati, Munisamy and Arabi, Oh, Arabi et al., Yu et al., Song et al., Du et al. and Walheer and

Zhang [7,25–31]. For the interest of space, in-depth examination of these methodological studies is omitted. In short, the methodological expositions modify the directional distance functions or the shape of the production possibility set of input and output space. Interested readers can refer to the studies mentioned.

Despite the abundant studies using the ML index, these previous studies do not distinguish the indirect or direct emissions of CO₂ in measuring green productivity growth. We emphasize that all the studies concentrate only on total emissions. This study fills this gap by considering the effect of indirect emissions on productivity growth, which is the main contribution of this study.

3. Methodology

As discussed in the previous section, this study investigates green productivity growth of the Korean industrial sectors by using the Malmquist-Luenberger (ML) productivity index. This section discusses the methodological aspects of the ML index.

3.1. The Directional Distance Function

Consider a panel of $k = 1 \dots K$ industries and $t = 1 \dots T$ time periods. The production technology for industries producing M desirable outputs, $\mathbf{y} \in R_+^M$, and J undesirable outputs, $\mathbf{b} \in R_+^J$, by using N inputs, $\mathbf{x} \in R_+^N$, is represented by the production possibility set (PPS), $P(\mathbf{x})$. The PPS is expressed as follows:

$$P(\mathbf{x}) = \{(\mathbf{y}, \mathbf{b}) \mid \mathbf{x} \text{ can produce } (\mathbf{y}, \mathbf{b})\} \quad (1)$$

In order to explain and model the production technology in which both the desirable and the undesirable outputs are jointly produced, several assumptions are required in the form of axioms. These axioms are as follows (See Färe et al. and Chung et al. [10,32]):

$$\text{if } (\mathbf{y}, \mathbf{b}) \in P(\mathbf{x}) \text{ and } 0 \leq \theta \leq 1, \text{ then } (\theta \mathbf{y}, \theta \mathbf{b}) \in P(\mathbf{x}). \quad (2)$$

$$\text{if } (\mathbf{y}, \mathbf{b}) \in P(\mathbf{x}) \text{ and } \bar{\mathbf{y}} \leq \mathbf{y}, \text{ then } (\bar{\mathbf{y}}, \mathbf{b}) \in P(\mathbf{x}). \quad (3)$$

$$\text{if } (\mathbf{y}, \mathbf{b}) \in P(\mathbf{x}) \text{ and } \mathbf{b} = 0, \text{ then } \mathbf{y} = 0. \quad (4)$$

$$\text{if } \bar{\mathbf{x}} \geq \mathbf{x}, \text{ then } P(\bar{\mathbf{x}}) \in P(\mathbf{x}). \quad (5)$$

See Färe et al. [10] and Chung et al. [32] for a detailed description of the above Equations (2)–(5).

The PPS that satisfies the above assumptions can be described in an output space, as illustrated in Figure 1. In order to simplify the methodological exposition, the case of one desirable output and one undesirable output case is illustrated. Without loss of generality, Figure 1 assumes that all industries use the same amount of inputs. The vertical axis represents a desirable output and the horizontal axis an undesirable output. All industries produce desirable and undesirable outputs within and on the solid outer line. Industries on the solid line are assumed to be producing on the production frontier, and these are used as the benchmark when calculating the DDF.

Figure 1. Distance function and the ML index.

The PPS can be remodeled using the DDF. Here, $\vec{G} = (\vec{G}_y, \vec{G}_b)$ is assumed to be a direction vector, where $\vec{G} \in R_+^M \times R_+^J$. Then, the DDF is defined as follows:

$$\vec{D}(\mathbf{x}, \mathbf{y}, \mathbf{b}; \vec{G}_y, \vec{G}_b) = \max \left\{ \beta \mid \left(\mathbf{y} + \beta \vec{G}_y, \mathbf{b} - \beta \vec{G}_b \right) \in P(\mathbf{x}) \right\}. \quad (6)$$

The DDF seeks to maximally increase desirable outputs while simultaneously decreasing undesirable outputs. The direction vector $\vec{G}$ determines the direction of the outputs in which desirable outputs increase and undesirable outputs decrease. In this study, the direction vector is chosen as $\vec{G} = (\mathbf{y}, \mathbf{b})$ following Chung et al. [10].

Since the ML index requires a heavy dose of additional notations, we prefer to ignore the direction vector $\vec{G} = (\mathbf{y}, \mathbf{b})$ in the DDF when defining and calculating the index in the remainder of this paper. For example, in all related aspects, we replace $\vec{D} = (\mathbf{x}, \mathbf{y}, \mathbf{b}; \mathbf{y}, \mathbf{b})$ with $\vec{D} = (\mathbf{x}, \mathbf{y}, \mathbf{b})$.

From Figure 1, the direction vector and DDF are illustrated with the decision-making unit (DMU) K . An arrow represents the direction of the DDF of the DMU K from the origin in a northwest direction. The DDF of the DMU K is represented as β . If a DMU is on the frontier (solid outer line), the DDF is zero. The β is considered as an inefficiency value. If the DMU is on the frontier, the inefficiency value is zero. In other words, this means it is operating under the highest efficiency.

3.2. ML Index

The ML index measures green productivity growth by accomplishing two targets: environmental protection and economic growth. We use this index to estimate the changes in green productivity under the condition of multi-inputs and multi-outputs between two time periods. The ML index has the advantage of simplicity when analyzing green productivity whilst the conventional Malmquist productivity index does not consider the environmental aspect. In addition, it only requires information on the input and output quantities and does not require market prices for such inputs and output variables. This virtue makes it easy to construct the data set in analyzing green productivity growth. In this setting, the common desirable outputs are chosen as factors that influence economic growth such as value-added, whereas undesirable outputs are chosen as factors that negatively influence the environment such as CO₂ emissions.

To estimate the ML index, the PPS needs to be reconfigured. Suppose that there are $t = 1 \dots T$ time periods; then, the PPS at time t is

$$P^t(\mathbf{x}) = \{(\mathbf{y}^t, \mathbf{b}^t) \mid \mathbf{x}^t \text{ can produce } (\mathbf{y}^t, \mathbf{b}^t)\}. \quad (7)$$

where the superscript t for each variable refers to the time period. Equation (7) is a PPS configured on the outputs and inputs of all industries observed during time period t . When the PPS is set as Equation (7), the ML index is expressed as follows:

$$ML^{t,t+1}(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t, \mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1}) = \left[\frac{1 + \vec{D}^t(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t)}{1 + \vec{D}^t(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1})} \cdot \frac{1 + \vec{D}^{t+1}(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t)}{1 + \vec{D}^{t+1}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1})} \right]^{\frac{1}{2}} \quad (8)$$

where the superscript on the DDF represents the time period of the PPS; the superscript on the input and output variables refer to the time period of observation for each input and output. For example, $\vec{D}^{t+1}(\mathbf{x}^t, \mathbf{y}^t, \mathbf{z}^t)$ measures the DDF of observation at time t compared to the PPS at time $t + 1$. The ML index thus incorporates the factors improving green productivity, and it can be decomposed as below:

$$\begin{aligned} & ML^{t,t+1}(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t, \mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1}) \\ &= \frac{1 + \vec{D}^t(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t)}{1 + \vec{D}^{t+1}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1})} \times \left[\frac{1 + \vec{D}^{t+1}(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t)}{1 + \vec{D}^t(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t)} \cdot \frac{1 + \vec{D}^{t+1}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1})}{1 + \vec{D}^t(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1})} \right]^{\frac{1}{2}} \\ &= \frac{TE^{t+1}}{TE^t} \times \left[TC_t^{t,t+1} \times TC_{t+1}^{t,t+1} \right]^{\frac{1}{2}} \\ &= EC^{t,t+1} \times TC^{t,t+1}. \end{aligned} \quad (9)$$

The first part of the productivity growth decomposition measures efficiency change, and the second part measures technical change. If inputs or outputs do not change between time periods t and $t + 1$, then $ML^{t,t+1} = 1$. In addition, $ML^{t,t+1} > (<) 1$ means that green productivity has improved (reduced) during time period t and $t + 1$.

The $EC^{t,t+1}$ measures the changes in technical efficiency between the two time periods. In other words, it measures how close a DMU moves towards the benchmark technology in time period $t + 1$ compared with time period t . If the DDF in the numerator of $EC^{t,t+1}$ takes a value of 0, the production observation is on the frontier at time t . If the value is greater than 0, the production unit is within the frontier and it is inefficient in time period t . $EC^{t,t+1} > 1$ indicates that a producer moves towards the frontier between t and $t + 1$ (i.e., the catching-up effect). $EC^{t,t+1} = 1$ indicates that a producer remains at relatively the same position within the frontier. Finally, $EC^{t,t+1} < 1$ indicates a producer is further from the frontier in time period $t + 1$ than it was in time period t .

The $TC^{t,t+1}$ measures the geometric mean of the shift in the frontier. This measures the technical change in the production of desirable and undesirable outputs. If the benchmark technology frontier shifts in the direction of more desirable outputs and less undesirable outputs, then $TC^{t,t+1} > 1$ (i.e., technical progress). If $TC^{t,t+1} = 1$, there is no shift in the production frontier. Finally, $TC^{t,t+1} < 1$ indicates a shift in the production frontier in the direction of less desirable outputs and more undesirable outputs, indicating technological deterioration.

3.3. Calculation of DDF

Various methodologies can be used in measuring the DDF. For these methods, see Chung et al., Lee et al., Kumar and Färe et al. [10,20,32,33]. In the present study, we implement the data envelopment analysis (DEA) linear programming technique. DEA easily describes multi-input and multi-output cases, and it is unnecessary to assume the statistical distribution of random errors. Also, it does not require *ex-ante* assumptions on the functional form of production or cost functions [34–39].

To calculate and decompose the growth in green productivity of industry k' between s and s' , we need to consider four equations that comprise a combination of the DDFs for two time periods t and $t + 1$. The DDFs are calculated by using the following equation:

$$\begin{aligned} \vec{D}^s(\mathbf{x}^{k',s'}, \mathbf{y}^{k',s'}, \mathbf{z}^{k',s'}) &= \max \beta \\ \text{such that,} \\ \sum_{k=1}^K \lambda^{k,s} y_m^{k,s} &\geq (1 + \beta) y_m^{k',s'}, \quad m = 1, \dots, M; \\ \sum_{k=1}^K \lambda^{k,s} b_j^{k,s} &= (1 - \beta) b_j^{k',s'}, \quad j = 1, \dots, J; \\ \sum_{k=1}^K \lambda^{k,s} x_n^{k,s} &\leq x_n^{k',s'}, \quad n = 1, \dots, M; \\ \lambda^{k,s} &\geq 0. \end{aligned} \quad (10)$$

where $\lambda^{k,s}$ is an intensity variable, indicating the intensity that an activity may be employed in the construction of the PPS. In the above equation, this represents the DDF of industry k' in period s' . For example, if $s = t$ and $s' = t + 1$, we can calculate $\vec{D}^t(x^{k',t+1}, y^{k',t+1}, z^{k',t+1})$. Likewise, if $s = t + 1$ and $s' = t$, we can calculate $\vec{D}^{t+1}(x^{k',t}, y^{k',t}, z^{k',t})$.

4. Description of the Data

This study examines the green productivity growth of 17 manufacturing sectors of Korea during the time period 2004 and 2010. The variables used for this empirical investigation were chosen as value-added, CO₂ emissions, energy consumption, labor force, and capital stock. Value-added was used as a proxy for desirable outputs, and CO₂ emissions as a proxy for undesirable outputs. The energy consumption, labor force, and capital stock were chosen as inputs of production technology. Because we were unable to collect data on capital stock in the Korean manufacturing industries, we used the amount of tangible assets at the end of each year as a proxy for the capital stock. In constructing the capital stock using such a framework, we needed to be very cautious in choosing an appropriate method between the total amount approach and the net amount approach. As [40] argues, evaluating capital stock on a net basis is more appropriate because the contribution of capital to profit generation tends to decrease over time. Therefore, in this study, tangible assets are used as the proxy of capital stock.

Data on value-added, CO₂ emissions, and energy consumption were collected from the Korea Energy Economics Institute (KEEI) and Korea Statistical Information Service (KOSIS), respectively. Labor force data were collected from the Bank of Korea, and data on capital stock were collected from Korea Enterprise Data (KED).

The descriptive statistics of variables are presented in Table 1. For all the variables, the mean is larger than the median, suggesting that variables are skewed to the right. This indicates that most industries are using fewer inputs and outputs.

Table 1. Descriptive statistics of the variables used in this study: 2004–2010.

	Mean	S.D.	Median	Max	Min
Value-added (in 100 billion KRW)	158.3	125.8	125.0	471.0	12.8
Total CO ₂ emissions (in thousands tCO ₂ e)	14,222.5	19,973.5	6995.3	287,108.6	1578.2
Direct CO ₂ emissions (in thousands tCO ₂ e)	9249.3	16,724.4	1862.1	179,060.8	145.0
Energy consumption (in thousands TOE)	5917.9	11,387.3	1645.6	52,937.9	371.3
Labor (thousands)	342.2	639.8	121.8	2824.4	8.7
Capital stock (in 100 billion KRW)	80.7	70.7	52.5	345.6	11.3

The level and growth rate for each input and output variables are listed in Table 2. The growth rate is calculated by using the compound annual growth rate (CAGR).

Table 2. Growth rates of input/output variables used in this study.

Industry	Value-Added (in 100 Billion KRW)		CO ₂ Emissions (in Millions tCO ₂ e)				Energy Consumption (in Millions TOE)		Labor (Thousands)		Capital Stock (in 100 Billion KRW)	
			Total		Direct							
	Mean	CAGR	Mean	CAGR	Mean	CAGR	Mean	CAGR	Mean	CAGR	Mean	CAGR
Textile	128.5	−0.7	9.6	−3.9	3.4	−9.8	2.3	−5.5	279.1	−3.4	70.1	1.7
Paper and Lumber	88.7	2.2	8.4	−1.6	2.7	−9.5	1.9	−3.3	129.3	0.1	52.9	6.9
Oil	74.9	−0.4	15.1	0.6	15.1	0.6	5.2	0.7	9.4	2.2	147.9	13.2
Petrochemical	351.8	4.0	49.7	5.0	31.2	4.4	46.6	4.6	389.3	1.9	186.4	8.7
Steel	221.8	3.1	80.4	6.4	67.3	5.7	21.3	6.1	113.4	4.0	71.0	15.8
Nonferrous	35.6	−1.6	3.7	6.7	0.6	7.4	0.8	6.8	38.6	1.4	30.5	11.5
Glass	39.9	13.8	3.1	3.8	1.6	−1.0	0.9	1.9	30.4	3.0	15.0	5.5
Ceramic	13.6	0	2.4	−11.5	1.8	−16.5	0.7	−10.9	28.9	0.5	16.8	3.8
Cement	38.4	−5.9	15.0	−0.3	12.1	−0.6	3.8	−0.5	41.8	1.2	32.2	6.0
Machinery	416.7	5.1	8.7	10.1	1.2	2.6	1.9	8.2	718.2	3.9	250.4	12.6
Semiconductor	214.1	17.9	5.6	12.6	0.2	3.1	1.1	10.8	125.5	1.2	39.2	17.1
Display	168.3	22.7	3.3	17.7	0.2	11.5	0.7	15.6	105.1	1.7	26.6	0.7
Electronic and Electricity	347.9	7.0	5.7	4.1	0.7	−12.6	1.2	1.5	451.6	1.3	132.9	8.0
Automotive	268.5	9.0	6.8	7.1	1.2	5.0	1.6	5.9	341.2	2.2	141.0	10.2
Shipbuilding	113.2	6.4	2.2	6.5	0.6	−6.1	0.5	3.3	146.4	9.0	36.3	21.5
Food and Tobacco	125.8	−0.9	6.4	1.5	2.5	−3.0	1.6	0.7	2791.0	0.0	102.7	8.2
Miscellaneous	44.0	3.2	15.6	5.9	14.6	6.0	8.2	4.6	78.4	1.0	20.3	9.5
Total	158.3	6.4	14.2	4.6	9.2	3.2	5.9	4.1	342.2	1.1	80.7	10.0

Value-added, as a proxy of desirable outputs, shows an average annual growth rate of 6.4%. The display industry has the highest average annual growth rate in value-added (22.7%), followed by the semiconductors (17.9%) and glass (13.8%). The machinery industry has the highest value-added (41,670 billion KRW), followed by the petrochemicals (35,180 billion KRW) and electronic/electricity (34,790 billion KRW).

The CO₂ emissions were divided into direct emissions and total emissions for productivity analysis in order to evaluate the policy scheme of Scope I and Scope II, respectively. The total emissions include direct and indirect emissions. Total emissions show an average annual growth rate of 4.6%. The steel sector has the highest total CO₂ emissions (80.4 million tCO₂e), followed by petrochemicals (49.7 million tCO₂e) and miscellaneous manufacturing (15.6 million tCO₂e). Ceramic (−11.5%), textile (−3.9%), paper and lumber (−1.6%), and cement (−0.3%) show the negative average annual growth rates. Direct emissions show an average annual growth rate of 3.2%. As similar with total emissions, the display industry has the highest average annual growth rate (11.5%), followed by the nonferrous metals (7.4%) and miscellaneous manufacturing (6.0%). The ceramic industry (−16.5%) shows the highest negative average annual growth rate. It is notable that the electronic/electricity, shipbuilding and food/tobacco show increases in total CO₂ emissions but decreases in direct emissions.

The average annual growth rate of energy consumption is 4.1%. Among all industries, the display industry shows the highest annual growth rate in energy consumption, followed by semiconductors (10.8%) and nonferrous metals (6.8%). The cement (−0.5%), paper and lumber (−3.3%), textile (−5.5%), and ceramic (−10.9%) industries have negative growth rates in energy consumption. Petrochemicals (46.8 million TOE) show the highest energy consumption among all industries. The average annual growth rate of the labor force is 1.1%, and shipbuilding (9.0%) shows the highest growth rate in labor force. The average annual growth rate of capital stock is 10.0%, in which the shipbuilding shows the highest growth rate in capital stock.

5. Empirical Results

We calculated the productivity growth for each sample industry and period by using the two emission yardsticks. As discussed above, the research focus is to evaluate the impact of the CO₂ reduction policy scheme. For this, we divided the empirical analysis into two parts in which CO₂ emissions were dealt with differently. The two analyses use the same value-added, labor force, energy consumption and capital stock variables, while they use different CO₂ emissions variables, i.e., total and direct emissions. To examine how indirect emissions affect each industry and the values of the DDF (inefficiency), we compared the productivity growth and its decomposed components.

5.1. The Measurement of DDF

The measurement of DDF represents how far an observation is from the frontier of PPS at a specific period. As discussed in the Methodology section, the DDF β , is a measure of the inefficiency of production when desirable and undesirable outputs are jointly produced. This measure tells us the percentage by which desirable outputs are increased or undesirable outputs are reduced in time period t . For example, if β equals 0.03, it is maximally possible to increase desirable outputs by 3% and reduce undesirable outputs by 3%. Therefore, for the non-zero values of β , the inversed value of $(1 + \beta)$ measures the efficiency of joint production. If the value of β is 0, it is unnecessary to change the current level of the desirable and undesirable outputs since the observation is on the frontier. Under this condition, efficiency of the joint-production is unity.

The DDF measurement results are listed in Table 3. The oil, steel, and semiconductor industries have β values of 0 for the two types of emissions, implying that the joint-production is fully efficient for both types of emissions. Some industries, such as ceramic and cement, have low values in efficiency for the two types of CO₂ emission yardstick.

Table 3. Value of the DDF and efficiency.

Industry	Total Emissions		Direct Emissions	
	β	Efficiency	β	Efficiency
Textile	0.6230 (0.0109)	0.6162	0.9202 (0.0140)	0.5208
Paper and Lumber	0.6581 (0.0354)	0.6031	0.8977 (0.0784)	0.5269
Oil	0.0000 (0.0000)	1.0000	0.0000 (0.0000)	1.0000
Petrochemical	0.6720 (0.1130)	0.5981	0.7970 (0.1773)	0.5565
Steel	0.0000 (0.0000)	1.0000	0.0000 (0.0000)	1.0000
Nonferrous	0.5472 (0.1996)	0.6463	0.5982 (0.2961)	0.6257
Glass	0.4122 (0.1361)	0.7081	0.4482 (0.1790)	0.6931
Ceramic	0.8167 (0.0292)	0.5504	0.9824 (0.0045)	0.5044
Cement	0.7694 (0.1540)	0.5652	0.8123 (0.1810)	0.5518
Machinery	0.0985 (0.0957)	0.9103	0.1823 (0.1520)	0.8458
Semiconductor	0.0000 (0.0000)	1.0000	0.0000 (0.0000)	1.0000
Display	0.0090 (0.0200)	0.9911	0.0147 (0.0329)	0.9855
Electronic and Electricity	0.0047 (0.0104)	0.9954	0.0058 (0.0129)	0.9943
Automotive	0.1863 (0.0387)	0.8429	0.4725 (0.1195)	0.6791
Shipbuilding	0.0303 (0.0348)	0.9706	0.0194 (0.0274)	0.9810
Food and Tobacco	0.5054 (0.0408)	0.6643	0.8931 (0.0281)	0.5282
Etc.	0.8942 (0.0173)	0.5279	0.9929 (0.0026)	0.5018

Note: The parentheses indicate the standard deviation.

It is notable that the β values for most industries using undesirable outputs as direct emissions are larger than those using total emissions, implying that measuring efficiency based on total emissions may be underestimated. The exception for this characterization is the shipbuilding industry, which shows lower inefficiency in total emissions than in direct emissions.

5.2. ML Index by Industrial Sector

We calculated the averages of green productivity growth, efficiency change, and technical change indexes for each industry, and results are listed in Table 4. For comparative purposes, the conventional Malmquist productivity index (M index) is also listed in Table 4.

Table 4. Productivity and decomposition results by industry.

Industry	Total Emissions			Direct Emissions					
	ML			ML			M		
	PC	EC	TC	PC	EC	TC	PC	EC	TC
Textile	1.0041	0.9998	1.0044	1.0038	0.9985	1.0054	1.0033	0.9490	1.1256
Paper and Lumber	1.0082	0.9975	1.0112	1.0094	0.9835	1.0281	0.9931	0.9424	1.0659
Oil	0.9906	1.0000	0.9906	0.9905	1.0000	0.9905	0.9474	1.0000	0.9474
Petrochemical	1.0060	0.9728	1.0355	1.0152	0.9581	1.0616	1.0011	0.9599	1.0570
Steel	1.0131	1.0000	1.0131	1.0112	1.0000	1.0112	0.9810	0.9446	1.0469
Nonferrous	1.0156	0.9526	1.0676	1.0064	0.9237	1.0949	0.9661	0.9515	1.0322
Glass	1.0791	0.9898	1.1015	1.1196	0.9994	1.0005	1.1143	1.0646	1.0639
Ceramic	1.0107	1.0067	1.0039	1.0014	1.0004	1.0009	0.9924	0.9637	1.0450
Cement	0.9836	0.9556	1.0301	0.9850	0.9494	1.0384	0.9331	0.9170	1.0297
Machinery	0.9812	0.9736	1.0093	0.9925	0.9335	1.0633	0.9812	0.9054	1.0897
Semiconductor	1.0429	1.0000	1.0429	1.0957	1.0000	1.0957	1.1357	1.0080	1.1269
Display	1.0284	1.0049	1.0232	1.1589	1.0081	1.1494	1.2410	1.0526	1.1899
Electronic and Electricity	1.0119	1.0005	1.0115	1.0483	1.0006	1.0477	1.0249	0.9511	1.1048
Automotive	1.0130	0.9967	1.0179	1.0341	0.9800	1.0627	1.0380	0.9705	1.0793
Shipbuilding	0.9751	0.9763	0.9987	0.9737	0.9423	1.0222	0.9213	0.8912	1.1195
Food and Tobacco	0.9948	0.9878	1.0073	1.0011	0.9938	1.0076	0.9171	0.9177	1.2114
Miscellaneous.	0.9990	0.9959	1.0031	0.9999	0.9994	1.0005	0.9795	0.9052	1.1246
Total	1.0070	0.9894	1.0190	1.0310	0.9779	1.0550	1.0210	0.9555	1.0950

Note: PC (Productivity change); EC (Efficiency change); TC (Technical change).

Based on total emissions, Korea's green productivity increased with an annual average growth rate of 0.7% during the study period. The result of this study is slightly lower than that of the previous studies. For example, Chung and Heshmati [14] found that Korea's industry green productivity increases by an annual average of 2.01% from 2001 to 2010. Green productivity increases in most sectors except for oil, cement, machinery, shipbuilding, and food/tobacco industries. Among the sample industries, the glass industry (7.9%) is the highest in green productivity growth, followed by semiconductor (4.3%) and display (2.8%). Shipbuilding (−2.5%) shows the lowest green productivity growth.

Based on direct emissions, green productivity increased by the annual average growth rate of 3.1%. Green productivity of direct emissions is higher than that of total emissions by about 2.4%p, originating from the fact that total emissions include indirect emissions. Under the hypothetical situation where all inputs and value-added are fixed, the level of carbon emissions is quite dissimilar across the two emission yardsticks. This dissimilarity is the main cause of the difference in green productivity growth. Also, this study's green productivity growth measurement result of direct emission is slightly higher than the result of Chung and Heshmati [14]. This result implies that only the total emission yardstick is likely to yield underestimated green productivity growth, which might guide policymakers to biased policy tools.

The display industry (15.9%) is the most productive industry, and the least productive industry is the cement industry (−1.5%). For most industries, the direct emission results show higher productivity growth than the total emission results. However, textile, steel, nonferrous metals, ceramic and shipbuilding showed the reverse result, i.e., the direction emissions show lower productivity growth than the total emissions. The fact that total emissions are higher than direct emissions signifies that the total emissions of the ML index should be lower than the direct emissions of the ML index. However, the five industries described above (textile, steel, nonferrous, ceramic and shipbuilding) are exceptions of this *a priori* conjecture mainly because these industries do not show significant differences between total emissions and direct emissions.

The average annual growth rate of efficiency is −1.1%, indicating a decline in efficiency. This finding means that the gap between the technology level of an average industry and the frontier technology has widened. This kind of efficiency decline arises in two possibilities: (i) The catching-up rate of an average industry is slower than the rate of the technological advancement of frontier industries, and (ii) when the rate of the technological deterioration of the frontier industries is slower

than that of an average industry. Since the technical change indexes for the two emission yardsticks are positive, the second possibility could be excluded from the main reason for the average efficiency decline. Ceramic, display, and electronic/electricity caught up to the frontier, whereas oil, steel, and semiconductor do not show an efficiency change. The remaining industries have an efficiency change smaller than unity, meaning that they lagged behind the benchmark frontier. The direct emissions result shows that the average annual growth rate of efficiency is -2.2% , which is less than 1.1% than the total emission yardstick. This difference in efficiency change between the two emission yardsticks suggests that the catching-up effect in total emissions is slightly faster than that in direct emissions.

The average annual rate of technical change in total emissions is 1.9% , indicating technical progress. This finding suggests that recently increasing concerns and policies about energy saving and environmental conservation have encouraged technology to be advanced. The glass industry (10.2%) has the highest positive technical change during the study period. Most industries increased technical change, whereas oil and shipbuilding industries are the exception. In direct emissions, the average annual growth rate of technical change is 5.5% . Also, technical progress has emerged in all industries except the oil industry during the study period.

Generally, these results show that Korea's green productivity has been significantly influenced by technical progress rather than technical catching-up effects. These results are similar to the results of the analysis on green productivity in Korea [8,14]. In addition, we see dramatic differences in green productivity growth when using different emission yardsticks, especially for the industries such as paper and lumber, petrochemicals, glass, cement, machinery, semiconductors, display, electronic/electricity, automotive, food and tobacco industries. This signifies that when we consider the emission data in green productivity measurement, only the usage of the total emissions data set is likely to yield biased results. Also, it is necessary to consider the characteristics of the industry and the effect of indirect emissions because it is likely to result in the duplication of emissions.

For comparative purposes, we measured the conventional M index which does not consider the effect of undesirable outputs. The average annual rate of the M index is 2.1% , indicating a productivity gain. The ML index is 1.4% lower than the M index, with especially large differences in the display and semiconductor industries. This result indicates that when policy target is related with CO_2 emissions, only the M index results might result in overestimation and biasedness.

5.3. Trend of the ML Index

The annual trends in green productivity growth rate, efficiency change and technical change for the total emission case are depicted in Figure 2. The green productivity decreases until 2008 and increases thereafter. The negative growth in the green productivity in 2007–2009 seems to come from the global crisis. Green productivity in 2004–2005 and 2009–2010 is higher than that in other years. The technical change trend also shows a similar trend to the green productivity, whilst the efficiency change trend does not. The efficiency change is greater in later periods than in earlier periods. Trends in green productivity growth, technical change and efficiency change tell us that the main contributor to the green productivity growth is technical change.

The trend of the three indexes for the direct emissions is depicted in Figure 3. This graph shows that green productivity decreases until 2007 and increases thereafter. This pattern is more distinct than the total emission result. Technical change also featured its lowest point in 2007–2008 and increased rapidly after 2008. Efficiency change showed its highest point between 2008 and 2009, but it is less than unity for the remaining years. Like total emissions, we can find that technical change is the main contributor to green productivity growth in the direct emission yardstick.

Annual cumulative green productivity and decomposition are shown in Figure 4, in which the left panel is for the total emission yardstick and the right panel is for the direct emission yardstick. The green productivity level increases by 4.5% in the total emission yardstick and 19.2% in the direct emission yardstick for the study period. The technology level increased by 12.2% in the total emission

yardstick and 37.2% in the direct emission yardstick. For the two emission yardsticks, technical change trends are very similar to that of green productivity growth. This also signifies that the main contributor to the green productivity growth is technical change. In the two emission yardsticks, we observe efficiency deterioration.

Figure 2. The trend of total emissions green productivity.

Figure 3. The trend of direct emissions green productivity.

Figure 4. Annual cumulative green productivity and decomposition for total emissions (left) and direct emissions (right).

5.4. Innovative Industries

Productivity growth and its decomposed sources fail to detect innovative industries which create new technologies by pushing the production frontier outwards. The reason for this ambiguity of detecting innovative industries comes from the fact that the technical change index of one industry can have positive value even if the industry is within the production frontier (For detailed discussion, see Oh and Heshmati [7]). As Färe et al. [37] argues, only economic agents on the frontier can innovate. To rule out the possibility of detecting economic agents within the production frontier in finding innovators, we need to set up the following procedure:

$$TC^{t,t+1} > 1 \quad (11)$$

$$\vec{D}^t(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{z}^{t+1}) < 0 \quad (12)$$

$$\vec{D}^{t+1}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{z}^{t+1}) = 0 \quad (13)$$

The in-detail interpretation is discussed in Oh and Heshmati [7].

Table 5 lists the innovative industries for each year. Regarding total emission, innovative industries rarely exist during the study period except for the oil industry from 2004–2005. Most industries fail to innovate because of the fact that they do not satisfy the conditions of Equations (12) and (13). This implies that technical progress has not occurred during the transition period, and most sample industries do not utilize frontier technologies. Concerning direct emissions, several industries are found to be innovative. These are shipbuilding, electronic/electricity, semiconductors, oil, and display industries. The semiconductor industry innovates for five times, followed by the display industry (four times).

Table 5. Innovative industries.

Year	Innovative Industry	
	Total Emissions	Direct Emissions
2004–2005	Oil	Display, Oil, Shipbuilding, Semiconductor
2005–2006	-	Display, Shipbuilding, Semiconductor
2006–2007	-	Display, Electronic/Electricity, Semiconductor
2007–2008	-	Electronic/Electricity
2008–2009	-	Electronic/Electricity, Shipbuilding, Semiconductor
2009–2010	-	Display, Semiconductor

6. Discussion and Conclusions

This study measured the green productivity growth and its decomposed sources of Korean manufacturing industries based on total emission and direct emission yardsticks for the period 2004–2010 in order to elaborate the effect of CO₂ emissions. The fact that this study examines the effect of indirect emissions is the main contribution of this study since most existing studies on green productivity growth of Korea have analyzed only the total emissions as undesirable output. To overcome these limitations, we measured the efficiency and productivity of 17 Korean manufacturing industries by distinguishing greenhouse gas emissions into total emissions and direct emissions using DDF and ML indexes. In addition, we compared results with the M index, which ignores environmental factors.

Empirical results show that: (i) The oil, steel, and semiconductor industries have the highest efficiency, while the efficiency of total emissions is higher than that of direct emissions except for the shipbuilding industry; (ii) green productivity in the manufacturing sector increased during the study period and the rate of productivity growth was significantly affected by technical change. Therefore, Korean manufacturing seems to have increased green productivity through technological innovation;

(iii) the productivity of both total emissions and direct emissions is lower than that for the M index; (iv) electronic/electricity and semiconductors were innovative industries for most of the study period for direct emissions, and (v) green productivity depends on the indirect emissions of each industry, implying that policy development needs to be made by considering these industrial characteristics.

Table 6 lists stylized measurement results for several previous studies on Korea's environmental productivity growth. The comparison between this study's results and previous studies Jeong and Lee, Chung and Heshmati, Aparicio et al. [8,14,22] tells us that the green productivity increased similarly during the study period. It also signifies that the main contributor to productivity growth is technical change. The difference between the current study and previous studies comes from the fact that (i) none of the previous studies considered the effect of indirect emissions, (ii) different time span for empirical investigation, and (iii) different categorization of industries. Although the magnitudes of the green productivity growth vary across previous studies and this study, an increasing pattern in green productivity is found.

Table 6. Stylized measurement results of Korean green productivity growth rate.

Study	Target	Periods	PC	EC	TC
This study	Korean Manufacturing 17 Industries	2004–2010	1.0070 (1.0310) ¹	0.9894 (0.9779) ¹	1.0910 (1.0550) ¹
Jeong and Lee (2011)	OECD 26 Countries	1991–2009	1.0010	0.9940	1.0080
Chung and Heshmati (2015)	Korean Industries	1981–2010	1.0175	1.0015	1.0160
Aparicio et al. (2017) ²	39 Countries	1995–2007	1.0058	1.0022	1.0056

Note: ¹ Parentheses indicate the results for direct emission; ² Aparicio et al. (2017) choose the initial years (1995–1996), middle years (2000–2001) and final years (2006–2007) as reference for detailed analyses. Their result in the Table 6 is the average value of the three periods.

Our empirical finding also suggest that certain industries may underestimate green productivity growth due to indirect emissions, or indirect emissions may cause problems such as redundant emissions. For this reason, characterizing industries based on direct/indirect emissions is the first step for elaborate policymaking since the choice of emission yardstick is likely to affect the green growth performance. Such an accurate analysis on the characteristics of emissions at the industry level helps policymakers develop appropriate policy tools.

Although this study is the first attempt at analyzing the effect of indirect emissions on green productivity growth, the following limitations remain. First, the sum of tangible assets for each industry is used as a proxy for capital stock. This proxy variable is not genuine capital stock, which might distort the measurement results. The industrial level capital stock data, such as KLEMS data, can be reformulated to be appropriate to the definition of our industrial classification. This challenging task is believed to yield more elaborate empirical findings. Second, the time span of our data set is limited. Since the direct and total emissions data set is confidential, we could not expand the time span to the most recent years. Third, the ML index employed in this study does not consider the progressive nature of technology. Because on this methodological limitation, technical deterioration was often observed. Sequential Malmquist index families, such as Shestalova and Oh et al. [41,42] are believed to resolve this problem.

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