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Environmental Performance Evaluation of the Korean Manufacturing Industry Based on Sequential DEA

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Abstract: This study's aim is to examine the environmental performance of the South Korean manufacturing industry and suggest performance-oriented policies. The manufacturing industry is classified into seven sub-sectors based on individual sectoral differences among firms. For this purpose, a sequential generalized directional distance function and the Sequential Malmquist-Luenburger (SML) index are used with the assumption of no deterioration in technology over time. The SML is decomposed into two indices: efficiency change (EC) and technical change (TC). The empirical results showed an average increase of 0.3% in environmental productivity measured by the SML over the whole period. Although the overall average value is low, it showed a 0.8% increase after 2015, implying that ETS policy has enhanced environmental productivity. From the decomposition of the SML, it was also found that the EC index (−1.1%) was comparatively lower than the TC index (1.5%) over seven years, implying that the innovation effect leads the environmental productivity of the Korean manufacturing industry. With regard to individual sectors, the seven sub-sectors showed quite different patterns in their performance. Therefore, not only should firms in each sector make an effort to enhance their performance, but the government also needs to support specialized measures to enhance firms' overall competitiveness.

Keywords: manufacturing industry; sectoral classification; Sequential DEA; environmental productivity; catching-up effect; innovation effect; customizing policy; Korea

1. Introduction

At the recent general assembly meeting of the Intergovernmental Panel on Climate Change (IPCC) at Songdo, on October 1, 2018, the IPCC unanimously approved the "Keeping global warming at 1.5 °C" special report [1]. According to this report, to limit the rise in average temperature to 1.5 °C until the year 2100, the 2010 Carbon Dioxide ('CO^2') emissions per year must be curtailed by 45% by 2030, and net zero emissions must be achieved by 2050. Therefore, it is an urgent challenge for the entire world to reduce CO_2 emissions in order to face the challenge of global warming. South Korea ('Korea') is one of the exemplary cases of this serious challenge, because the country was ranked the seventh highest emitter in the world in 2017. In addition, according to the Organization for Economic Cooperation and Development (OECD) environmental performance reviews (2017) [2], Korea has recorded the 2nd most rapid growth rate for its Greenhouse Gas ('GHG') emissions among OECD countries. As we can see from these data, Korea needs to make more proactive efforts to overcome the stigma of being an "environmentally underdeveloped country." Nonetheless, it also seems that it will be difficult to achieve the ambitious Korean target set at the 21st Conference of Parties meeting in December 2015, i.e., of cutting business as usual carbon emissions by 37% by 2030 [3]. Especially, there has been strong resistance to this ambitious target from a group of passive firms, implying that environmental policies may lack the governance or workable mechanisms required to achieve sustainable performance.

Thus, it is important to balance economic and environmental effects to achieve sustainable growth. For this purpose, Korea has been working on reducing national GHG emissions. One of these efforts is based on regulating economic activities with a nationwide Emission Trading Scheme (ETS) implemented in 2015. The scheme provides emission limits for all major emitter industries, with particular limits for the manufacturing sector. It is based on a market-oriented approach; under this environmental regime, every firm is allocated an emission allowance by the government. However, firms can buy or sell permits when they face a shortage or surplus of emission allowances [4]. The ETS covers 5 sectors and 23 sub-industries; 525 firms joined the ETS in 2015, accounting for 66% of CO^2 emissions produced in Korea [3]. Among the 5 major sectors, the manufacturing industry sector contributes 30.4% of the Gross Domestic Production (GDP) and 27.5% of GHG emissions in Korea [5]. Furthermore, Korean manufacturing industry was ranked 5th in the world in 2017, with value added 422,064.51 US dollar [6]. Thus, the Korean manufacturing industry is closely related to national competence, and is therefore the focus of this study. Moreover, in order to face the current serious challenges from China in the form of extremely competitive costs, the manufacturing industry needs to acquire a more advanced environmentally competitive structure. Nevertheless, there is little literature to date exploring this industry from an environmental perspective, especially on the individual company level.

To manage GHG emissions in the manufacturing industry, the Korean government introduced ETS. Therefore, it is very important to evaluate the feasibility of ETS policies on manufacturing companies. As the ETS proposes a "top-down approach" by the Korean government, it raises the following intrinsic questions for its sustainable performance: Will the ETS be helpful in maintaining national competitiveness? Are emission allocations for each sector reasonable? Which sectors are more beneficial or detrimental to the environment under the current ETS scenario?

To answer all these questions and make feasible suggestions for environmental policies, in the first stage, we analyze the effect of ETS policies on environmental productivity, while in the second stage, we focus on the determinants of environmental productivity. In the first stage, we shall focus on the policy effects on the manufacturing industry over time, because there may be some bias in the top-down approach of the ETS, and thus, the selective limits may work better, at least in the initial stage of ETS. In the second stage, we aim to develop some practical proposals for selective concentration policies. A top-down approach on the ETS target for the manufacturing industry may result in the overload or shortage of individual emission abatement potentials, implying the need for more customized regulatory policies on the subsectors of the manufacturing industries based on the individual conditions and internal characteristics of the sub-sectors of the manufacturing industry. To find out more customized solutions on the individual company level, we adopt the directional distance function (DDF) to evaluate the environmental performance of the manufacturing sub-industry sectors over the last seven years.

This study hopes to make the following unique contributions. First, a top-down approach by the Korean government may not result in effective GHG emission abatements due to a lack of field-oriented customization on the regulatory targets in terms of emissions. In order to evaluate this biased effect on manufacturing sub-industries, we use individual company-level data and their emission volumes in this field. To the best of our knowledge, very few studies [4,7,8] have used these data up to now. For this perspective, in this research, recent company-level data is used. This may help to enhance the reliability of empirical results and the resulting policy suggestions in terms of more-company or sub-industry level perspectives. Second, the seven years of data cover almost all manufacturing sectors, which provides more implications than a single-industry or cross-sectional approach. This panel data analysis may highlight the driving factors of the trends of environmental performance, and may also provide cross-sectional benchmarking suggestions. From this panel evaluation, the most efficient company in the group, as well as in the whole manufacturing industry, shall be found as the benchmarking case for the catch-up and innovation effects. These more specific, customized suggestions on the individual company level shall be the most important unique contribution of the research. Third, from a methodological perspective, we adopt the concept of sequential generalized DDF (SGDDF), which is suitable for reflecting environmentally-sensitive production in more field-oriented terms. To the best of our knowledge, this is the first trial adopting this methodology to focus upon the Korean manufacturing industry.

2. Literature Review

The DDF approach has been widely used in the Environment and Energy fields (E&E) to analyze efficiency or productivity in specific industries and regions [8–16]. This is because it has the capacity to expand desirable outputs while reducing inputs and undesirable outputs. This characteristic is suitable for the ultimate goals in the E&E field. There are two types of distance functions: the Shephard distance function [17] and the DDF proposed by Chambers et al. [18]. The former is limited because it analyzes desirable and undesirable outputs at the same rate. It cannot reflect conjointness. The latter overcomes this limitation by expanding desirable outputs and reducing undesirable outputs simultaneously. Thus, the DDF is a generalized form of the Shephard distance function and is more powerful and flexible [19].

Although the DDF seems to be the more appropriate methodology for this study, Shestalova [20] highlighted yet another limitation in standard data envelopment analysis (DEA). According to Shestalova, in the standard DEA approach, the production frontier could move inward, implying a "technical regression." This assumption is not appropriate for the manufacturing industry, because a decline in productivity in this industry could be a temporary phenomenon; and technological deterioration could induce a confusing result. To overcome this limitation, Shestalova [20] adopted Sequential DEA to evaluate TFP growth of manufacturing industries in 11 OECD countries, and compared this result with contemporaneous DEA data. Beyond this research, there have been numerous studies adopting concept of Sequential DEA in exploring environmental performance. Oh and Heshmati [21] also focused on excluding technical regress, and suggested the use of the Sequential Malmquist Luenburg (SML) index to examine the productivity of 26 OECD countries with panel data (1970–2003). Zhang and Kim [22] used a sequential slack-based measure (SSBM) model to analyze Korean power companies from 2007 to 2011, and, using same model, Choi and Wang [23] explored the land use efficiency of Korean 16 local governments from the period 2006–2013. Yu et al. [24] used sequential meta-frontier Luenberger productivity index (SMLPI) to explore coal-fired Chinese power plant from 1999–2008, Wu et al. [25] adopted the SML index to examine 30 Chinese provinces from 1996–2015. Zhang et al. [26] explored the sustainability performance of China from the period 2001–2010 based on Sequential Generalized Directional Distance Function (hereafter SGDDF), which is an extended version of the Generalized Directional Distance Function (hereafter GDDF). These studies exploring environmental performance commonly adopt undesirable outputs such as CO2, GHG and pollution.

Because the aim of this study is to evaluate the overall environmental performance of the Korean manufacturing industry from a more dynamic perspective, we will analyze the overall, as well as sub-sectoral manufacturing industries', performance in a stepwise approach. Here, Dynamic perspective stands for analysis with time-series data. It is different from cross sectional analysis, in that it is possible to focus on performance change over times. In the first stage, the environmental efficiency shall be derived based on the SGDDF on the manufacturing industry. In the second stage, we examine the governing factors of this dynamic change in the Korean manufacturing industry by using the Sequential Malmquist-Luenberger (SML) index. In this second stage, we not only find the feasible factors influencing environmental productivity, but also the innovator companies for each sub-sector industry. In order to find the determinant factor in the second stage, we shall decompose the SML into efficiency change ('EC') and technology change ('TC'). However, we assume that even in the manufacturing industry, different individual characters exist among sub-sectoral industries, and thus, we may find the over- and sub-sectoral determining factors between EC and TC. If a sub-sectoral industry outperforms in EC, the catch-up effect is much more important to enhance its environmental performance. Based on this argument, we shall propose that the leader companies may serve as the benchmark for less productive companies. For the same reason, if a sub-sector outperforms in TC, it should find the leading innovative company to enhance its productivity. Therefore, at the end of the second stage, we report on innovative companies in each sector that are worthy of benchmarking using the concept of technical change.

3. Methodology

3.1. Environmental Production Technology

Based on the traditional approach to production function, the model begins with the basic three inputs: capital (*K*), labor (*L*), and energy consumption (*E*). These inputs generate a desirable output of sales turnover (*T*) and an undesirable output of GHG (*C*) emissions. In this study, GHG will be expressed as '*C*', since almost all studies have used carbon as an undesirable output. This production technology can be expressed as follows:

$$T=\{(K,L,E,T,C):(K,L,E) \text{ can produce } (T,C)\} \quad (1)$$

where T is assumed to satisfy all the standard axioms of the production theory [27]; that is, inactivity is always possible, and finite amounts of a given input can produce only finite amounts of output. In addition, an input and a desirable output are often assumed to be freely disposable. Concerning the regulated environmental technologies, weak disposability must be imposed on T. We can express this assumption as follows:

$$\text{(i) If } (K,L,E,T,C) \in T \text{ and } 0 \leq \theta \leq 1, \text{ then} (K,L,E,\theta T,\theta C) \in T$$

$$\text{(ii) If } (K,L,E,T,C) \in T \text{ and } C=0, \text{ then } T=0$$

The weak disposability assumption (i) implies that reducing GHG emissions is costly. It entails an opportunity cost measured by the proportionate reduction in sales turnover. The null-jointness assumption (ii) implies that GHG emissions inevitably accompany the production process.

3.2. The SGDDF

Based on the above assumptions, environmental production technology (T) can be introduced in a more detailed functional form. According to Färe and Grosskopf [28], we define the GDDF as follows:

$$\vec{D} = \max\,(\beta_1 + \cdots + \beta_m + \gamma_1 + \cdots + \gamma_s + \alpha_1 + \cdots + \alpha_j)$$

$$s.t. \sum_{n=1}^{N} \lambda_n x_{in} \leq x_{i0} - \beta_i \mathrm{g}_i$$

$$\sum_{n=1}^{N} \lambda_n y_{rn} \geq y_{r0} + \gamma_r \mathrm{g}_r$$

$$\sum_{n=1}^{N} \lambda_n b_{jn} = b_{j0} + \alpha_j \mathrm{g}_j$$

$$\lambda_n \geq 0, n = 1,2, \ldots, N$$

$$\beta_i \geq 0, \gamma_r \geq 0, \alpha_j \geq 0$$

$$i = 1,2, \cdots, m;\ r = 1,2, \cdots, s \tag{2}$$

In Equation (2), $g_i, g_r,$ and g_j are explicit directional vectors in which the input/output combination is scaled. β_i and γ_r are scaling factor vectors. Although the directional vector g is set as (1, 1) for inputs and outputs respectively, it lacks the unit invariant property in this setting. Therefore, following Chung et al. [29] and Zhou et al. [30], this study selected the observed value as the directional vector. However, the GDDF is estimated separately for each time period *t*, and this is often translated into wide oscillations [26]. Therefore, as suggested by Zhang et al. [26], we adopted sequential technology as in Equation (3). This estimates each period not only for the current year, but also for all the preceding years.

$$\overrightarrow{D_S} = \max\ (\beta_1 + \cdots + \beta_m + \gamma_1 + \cdots + \gamma_s + \alpha_1 + \cdots + \alpha_j)$$

$$s.t. \sum_{T=1}^{T}\sum_{n=1}^{N} \lambda_n^T x_{in}^T \le x_{i0}^T - \beta_i g_i$$

$$\sum_{T=1}^{T}\sum_{n=1}^{N} \lambda_n^T y_{rn}^T \ge y_{r0}^T + \gamma_r g_r$$

$$\sum_{T=1}^{T}\sum_{n=1}^{N} \lambda_n^T b_{jn}^T = b_{j0}^T + \alpha_j g_j$$

$$\lambda_n^T \ge 0, n = 1,2,\ldots,N$$

$$\beta_i \ge 0,\ \gamma_r \ge 0,\ \alpha_j \ge 0$$

$$i = 1,2, \cdots, m;\ r = 1,2, \cdots, s \tag{3}$$

where λ_n^T is an (N × 1) vector representing the intensities assigned to each observation in constructing the sequential environmental technology for the current period *t*.

In both the GDDF and SGDDF, the author can set vector g freely, based on academic goals. If $\vec{D} = 0$, then it would indicate that the firms are located along the best-practice frontier in the g direction. From these two DDFs, we will first derive firm efficiency, and then, as the next step, derive environmental productivity using the SML concept.

3.3. SML Index and Its Decomposition

Based on the SGDDF result, the second stage focuses on determining the governing factors of these results. To examine the factors that contribute to the dynamic change in environmental efficiency, we analyze the decomposition of efficiency over time using the Malmquist-Luenburger (ML) index. As already stated, this study's aim is to evaluate environmental productivity using the SML index. Therefore, we should define the ML index first. Equation (4) defines the conventional ML index [29].

$$ML^s = \frac{(1+\vec{D}_c^s(x^t, y^t, b^t))}{(1+\vec{D}_c^s(x^{t+1}, y^{t+1}, b^{t+1}))} \tag{4}$$

where the contemporaneous DDFs, $\vec{D}_c^s(x, y, b) = \max\ \{b: (y + \beta\, y, b - \beta\, b) \in P^s(x)\}$, s = t, *t*+1, are defined on each of the contemporaneous production possibility set (PPS) at the time period *s*. *c* in the DDF implies "contemporaneous."

However, the sequence reference is different. The frontier consists of the decision-making units (DMUs) of the current period and all previous periods, and DMUs constructing the frontier of period *t*+1 contain the DMUs of period *t*. Compared with period *t*, therefore, the frontier of period *t*+1 will certainly not move backward, which is an important characteristic of the sequential

Malmquist model. As a result, based on Oh and Heshmati [21], we redefine the SML index as follows:

$$SML^{s}=\frac{(1+\vec{D}_{q}^{s}(x^{t},y^{t},b^{t}))}{(1+\vec{D}_{q}^{s}(x^{t+1},y^{t+1},b^{t+1}))} \tag{5}$$

Meanwhile, the geometric mean form of the SML productivity index can be decomposed into the EC and TC indices as follows:

$$SML^{t,t+1}=\frac{1+\vec{D}_{q}^{t}(x^{t},y^{t},b^{t})}{1+\vec{D}_{q}^{t+1}(x^{t+1},y^{t+1},b^{t+1})}$$

$$\times\left[\frac{1+\vec{D}_{q}^{t+1}(x^{t},y^{t},b^{t})}{1+\vec{D}_{q}^{t}(x^{t},y^{t},b^{t})}*\frac{(1+\vec{D}_{q}^{t+1}(x^{t+1},y^{t+1},b^{t+1})}{1+\vec{D}_{q}^{t}(x^{t+1},y^{t+1},b^{t+1})}\right]^{1/2}$$

$$=\mathrm{EC}^{t,t+1}\times\mathrm{TC}^{t,t+1} \tag{6}$$

The EC index in Equation (6) measures the "catching-up" effect denoting the environmental efficiency changes for a DMU (firm) between the period *t* and *t*+1. EC captures the movement of a DMU toward the contemporaneous environmental benchmark frontier. If EC > 1, it means that there is an efficiency gain between *t* and *t*+1, and vice versa (efficiency loss) if EC < 1. If EC = 1, it means there is no efficiency change in consecutive years. That is to say, EC stands for distance change between specific DMU and efficient frontier. The TC index measures how much a frontier shifts between period *t* and *t*+1. If TC > 1, then technical change enables more production of desirable outputs and less production of undesirable outputs. The TC index measures frontier shifts in contemporaneous technology; hence, it is regarded as an innovation effect. However, as mentioned, TC is always more than value '1' in this study. This is because there is an assumption of 'no technical regress' under sequential DEA.

3.4. Innovative Firms

According to Färe et al. [31] and Oh and Heshmati [21], the three conditions for determining innovator firms are as follows:

$$\mathrm{TC}>1 \tag{7}$$

$$\vec{D}_{q}^{t}(x^{t+1},y^{t+1},b^{t+1})<0 \tag{8}$$

$$\vec{D}_{q}^{t+1}(x^{t+1},y^{t+1},b^{t+1})=0 \tag{9}$$

Equation (7) means that the group technology frontier moves towards the direction with more outputs that are desirable and less that are undesirable, that is, period *t*+1 shows better performance than period *t*. Equation (8) means that the production activity of innovative firms during the period *t*+1 should be outside the group technology frontier in period *t*. In Equation (9), an innovative firm should be located on the group technology frontier in period *t*+1. Based on these three equations, we will report the group innovator firms of each sector for seven years in this study. These firms could be good models for the rest of the sector to benchmark to enhance their environmental performance. Thus far, we have reviewed the methodology that we will use in this study.

4. Characteristics of Data and Empirical Results

4.1. Data and Their Characteristics

In order to examine the environmental performance for Korean manufacturing industries, the data of 289 manufacturing firms belonging to seven sectors were collected for 2011–2017. As the output variables, we selected sales turnover (T) as the desirable output and GHG (C) as the undesirable output. As the input variables, we set two basic types of inputs, labor (L) and capital

(K), and included energy (E) as the third input because it has a very significant effect on GHG emissions. The data for labor, capital, and turnover were retrieved from the Data Analysis, Retrieval, and Transfer System. The energy and GHG emission data were taken from the Greenhouse Gas Inventory & Research Center of Korea. In general, studies on the E&E field have extracted pure CO_2 values under the IPCC guidelines by using a macro type of data such as fuel [14,15] consumption rate. However, CO_2 data were unavailable in Korea; thus, we used the numeric values from the GHG emissions data, which includes other gases such as methane, nitrogen, hydrofluorocarbons, perfluorinated compounds, and sulfur hexafluoride.

With regard to industries, the mining, wood, and oil industries were not included because of a scarcity of data. Additionally, it was impossible to cover all firms because of the unavailability of data. A total of 289 firms were obtained by this process. Table 1 shows the descriptive statistics of this study.

Table 1. Descriptive statistics.

Variable	Type	Unit	Mean	Std. Dev.	Max.	Min.
Sales turnover	Desirable output	KRW Million	2,318,087	9,589,316	161,915,007	7,577
GHG (Greenhouse gas)	Undesirable output	CO_2 equivalent tons	697,465	4,593,449	77,246,111	2,129
Capital	Input	KRW Million	117,807	327,136	3,657,652	100
Labor	Input	Per person	2,297	8,061	101,970	29
Energy	Input	Terajoules	8,149	41,902	864,884	41

Sources: Greenhouse Gas Inventory & Research Center of Korea (http://www.gir.go.kr/) [32]. DART: Data Analysis, Retrieval, and Transfer System (http://dart.fss.or.kr/) [33]

Every sector has its own unique characteristics; thus, classifying groups based on heterogeneity, as some previous researchers did [20,34–36], seems to be more practical. Therefore, we also classified the sectors in the Korean manufacturing industry based on Shestalova [20], because it gives a feasible way to analyze the manufacturing sectors in more practical terms. However, because her study did not include high-tech sectors such as electronic devices, displays, and semi-conductors, we created a new group called "ELE" including them. This ELE sector could be very important in the categorized analysis, as it will give us a sustainable signal on the environmental policy effect on the Korean economy. Figure 1 shows the shares of seven individual groups, and Table 2 shows details of the sub-industries in each group in this study.

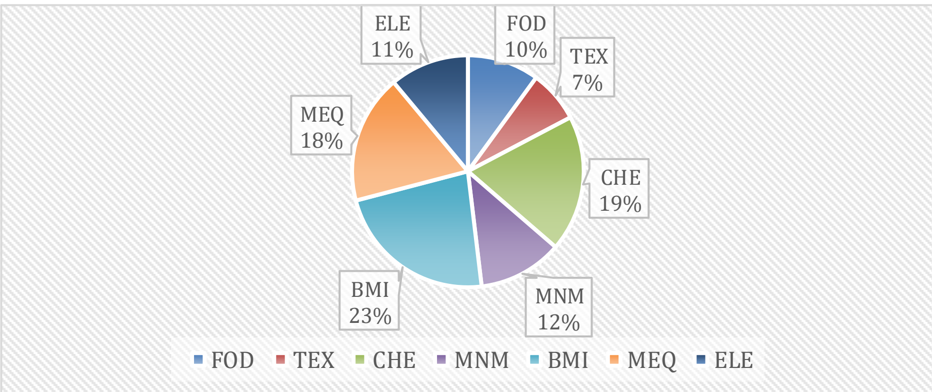

Figure 1. Seven groups and the percentage share of firms in each group.

Table 2. Seven groups and their sub-industries.

Groups	Sub-Industries
FOD	Food, beverage, and tobacco
TEX	Textiles, wearing apparel, and leather industries
CHE	Chemical, chemical petroleum, coal, plastic, and rubber
MNM	Non-metallic, mineral products except products of petroleum, and coal
BMI	Basic metal items
MEQ	Fabricated metal, machinery, and transportation equipment
ELE (added by author)	Electronics, semiconductors, and displays

From this classification, we finally evaluated the environmental efficiency and productivity based on the SML and its decomposition (EC, TC) and identified the innovator firms in each sector.

4.2. *Empirical Results and Their Implications*

This study follows a stepwise approach. In the first stage, we derive the environmental efficiency value based on the GDDF and SGDDF. The purpose of deriving two indices simultaneously is to investigate whether adopting a "sequential DDF" is reasonable. For this purpose, we should check whether the two efficiencies show an a priori difference. If not, the adopted methodology is inappropriate for our purpose. Based on Equations (2) and (3), respectively, the average value of the GDDF was 0.686 and SGDDF was 0.641 for the sample period of seven years. This proves that the GDDF could overestimate the real efficiency, and that the SGDDF reflects the field-oriented phenomena more reasonably. To support statistical differences between GDDF and SGDDF, we conducted a Mann-Whitney test to check the null hypothesis of no group difference. As shown in Table 3, the M-W test statistic shows a *p*-value of 0.000, and we can reject the null hypothesis, concluding that there is a significant difference between GDDF and SGDDF.

Table 3. Result of Mann-Whitney test.

Test	Null Hypothesis	Test Statistic	*p*-Value
Wilcoxon-Mann-Whitney	Mean(GDDF) = Mean(SGDDF)	1,707,724	0.000

Because the efficiency value of 1 implies perfectly efficient conditions, the empirical average value of 0.641 implies that there is potential for 35.9% improvement in the efficiency of the Korean manufacturing industry. This implies huge potential for companies to become more competitive in sustainable management. Furthermore, there is scope for appropriate government polices promoting sustainability to reduce this gap.

In the second stage, based on Equation (5) in Section 2, we derived the SML index to examine the governing factors to reduce this inefficiency gap by 35.9%. Table 4 and Figure 2 shows the empirical results of each sector and the average values for the period 2011–2017. All the individual manufacturing companies are categorized into the 7 sub-sectors, as shown in Table 2. The result shows a discouraging downward trend in the SML for all sectors during the period 2011–2015, implying that environmental efficiency did not improve before the implementation of the ETS. However, it shows an upward trend after 2016. Thus, the whole sample period shows a U-trend, clearly indicating the effectiveness of the ETS policies since their implementation in 2015.

Table 4. Average value of the Sequential Malmquist Luenburg index.

Sector	2011–2012	2012–2013	2013–2014	2014–2015	2015–2016	2016–2017	Average
FOD	1.035	1.013	0.980	1.007	1.011	0.984	1.005
TEX	0.971	0.984	0.972	1.032	1.022	1.012	0.999
CHE	1.008	0.999	0.975	0.966	0.992	1.038	0.996
MNM	1.017	1.019	1.054	0.988	1.011	1.021	1.018
BMI	0.992	0.982	0.987	0.988	0.991	1.025	0.994
MEQ	0.996	0.991	0.993	1.000	0.992	0.995	0.994

ELE	0.982	1.004	0.998	1.005	1.033	1.066	1.015

On average, the SML index of all sectors increased by approximately 0.3%, implying that the total environmental productivity of the Korean manufacturing industry increased during the 2011–2017 period. If we focus on the period from 2015, the average SML index increased to 0.8%, which is much higher because of the ETS policies. Although the SML index showed a decrease (0.998) until the first year of the ETS, it started to increase (J-curve effect) from 2016. This is a noteworthy result because environmental productivity has increased as environmental regulations settled. It partially supports the Porter hypothesis [37], implying that strict environmental regulation increases efficiency and encourages innovation efforts towards more environmentally-friendly production processes. Hence, although it has been just three years since its implementation, we can say that the ETS has shown a positive effect on environmentally-friendly productivity, and it will be helpful in advancing the Korean economic structure if it strengthens its regulatory policies.

Meanwhile, we also need to focus in more detail on each of the seven sectors' performances, because each one has a different input-output structure. On the seven-year average, the result shows quite different performances: FOD (0.5%), TEX (−0.1%), CHE (−0.4%), MNM (1.8%), BMI (−0.6%), MEQ (−0.6%), and ELE (1.5%). This result implies that MNM, ELE, and FOD are the leading sectors during the sample period. However, we should pay more attention to the productivity change after 2015. After 2015, most sectors, with the exception of MEQ, show an average efficiency less than 1, but still higher than before. Especially, the CHE and BMI sectors show an impressive upward trend for 2016 and 2017. Therefore, the implementation of the ETS had a positive effect on each industrial sector, even if their effects are quite different from each other. Although MEQ shows lower productivity for all the sample periods, it does not indicate an adverse effect of the ETS, as it maintains a stable productivity value.

In general, the two leading sectors, CHE and BMI, are capital- and energy-intensive sectors. The ELE sector showed a particularly outstanding upward trend for its environmental performance as well. Therefore, this might imply that the ETS policies result in a more positive effect on capital-intensive industries. As capital- and energy-intensive industries contribute a major share to the overall GHG emissions, it could be a good signal that transformation to environmentally-friendly sustainable development is feasible and successfully workable.

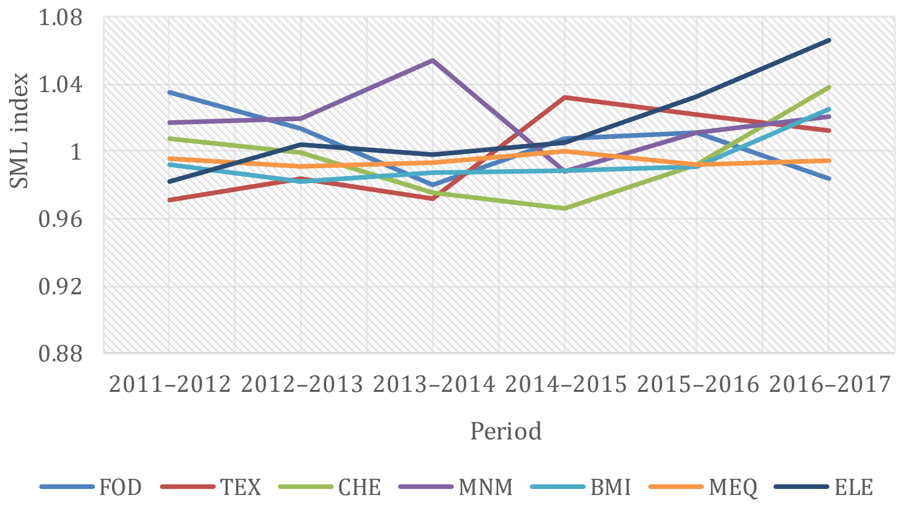

Figure 2. Changes in the Sequential Malmquist Luenburg index.

As mentioned above, we decomposed the SML index into two indices, EC and TC, to examine productivity-governing factors. As the SML value is derived from the EC and TC, we could deduce each sector's characteristics and its main causes (driver) for productivity.

The average EC index of the entire Korean manufacturing industry is 0.989, which implies that an average decrease (−1.1%) in efficiency exists. The EC index measures how much a company as a DMU in a specific group increases its efficiency every year. This is called the 'catching-up' effect. Only ELE shows a comparatively higher value (1.006) for all seven years, while the rest of the sectors show less than 1. They ranged from 0.983 to 0.992, which implies a decrease in the catching-up effect. This negative EC index result means that the Korean manufacturing industries show the digital divide between IT and other industries, and thus, the rest of the sectors need to be more active in finding solutions to enhance their comparative efficiency. Certainly, the government promotion of policies will encourage their efforts toward frontier efficiency and a faster catching-up effect. Using public incentives to improve managerial operations and benchmarking the best practices from efficient firms in their group might be optimal. Similar to the SML index, the EC index dynamic trends in 2016–2017 show the highest result, indicating the effect of the 2015 launch of the ETS on the catching-up effect. It is especially noteworthy to analyze the CHE, BMI, and ELE sectors, as they show an extreme increase in the EC index in Table 5 and Figure 3.

Table 5. Average value of the Efficiency Change index.

Sector	2011–2012	2012–2013	2013–2014	2014–2015	2015–2016	2016–2017	Average
FOD	0.950	0.974	0.980	1.006	1.011	0.979	0.983
TEX	0.971	0.968	0.972	0.972	0.996	1.012	0.981
CHE	0.999	0.982	0.974	0.966	0.992	1.038	0.992
MNM	0.982	0.999	1.008	0.977	0.956	0.999	0.987
BMI	0.981	0.943	0.986	0.988	0.991	1.025	0.986
MEQ	0.987	0.988	0.992	0.999	0.992	0.992	0.992
ELE	0.977	0.999	0.997	1.004	0.995	1.062	1.006
Average	0.978	0.979	0.987	0.984	0.989	1.015	0.989

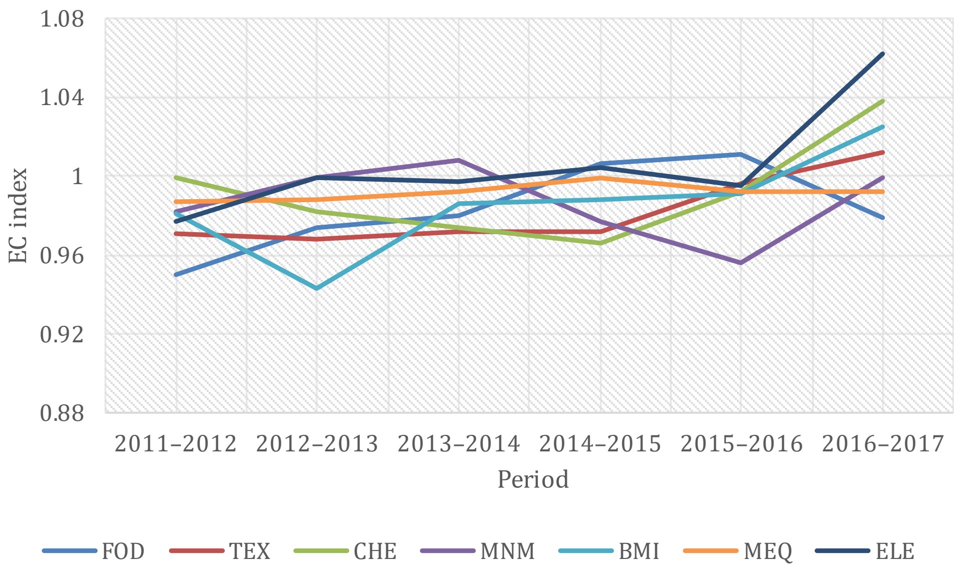

Figure 3. Changes in the Efficiency Change index.

The TC index indicates a change in the technology (innovation effect). As you can see in Table 6, the average TC value of the Korean manufacturing industry is 1.015; this means that the average innovation effect over seven years is just 1.5%. It is noteworthy that TC values range from 1 to 1.090. As this study has adopted the SGDDF concept, it assumes there is no technical regression. In Table 5, we can see that sector MNM shows the best performance in TC because it maintains values of more than 1% over the seven years. The ELE sector was also regarded as beneficial to the environment because its values increased dramatically after 2015. We also found that the TC values were higher than the EC values, indicating that the TC index has a more significant influence on the positive effect of the SML. Thus, we can say that the innovation effect is the main driver of environmental productivity.

Table 6. Average value of the Technical Change index.

Sector	2011–2012	2012–2013	2013–2014	2014–2015	2015–2016	2016–2017	Average
FOD	1.090	1.041	1.000	1.001	1.001	1.005	1.023
TEX	1.001	1.017	1.000	1.095	1.000	1.000	1.019
CHE	1.008	1.018	1.001	1.000	1.000	1.000	1.005
MNM	1.035	1.019	1.045	1.011	1.070	1.022	1.034
BMI	1.016	1.045	1.001	1.000	1.000	1.000	1.010
MEQ	1.009	1.003	1.000	1.002	1.000	1.003	1.003
ELE	1.006	1.007	1.004	1.004	1.014	1.014	1.009
Average	1.024	1.021	1.007	1.016	1.010	1.005	1.015

So far, we have examined the SML index and its two decomposed indices (EC and TC). The next step is to identify the most innovative firms in each sector to explore which firms are leaders with respect to environmental productivity and innovation based on Equations (7)–(9), Firms identified as group innovators here are outstanding in their specific sectors. Table 7 reports innovative firms.

Table 7. Group innovators.

Industry (No. of Firms)	Group Innovators					
	2011–2012	2012–2013	2013–2014	2014–2015	2015–2016	2016–2017
FOD (2)		Lotte Food SPL			SPL	
TEX (2)				Korea Vilene		Daenong
CHE (4)	Daelim industry, Hyundai EP	Namhae chemical	Jaewon Industry			
MNM (3)			Daehan Ceramics, Wooryong, KCC			Wooryong
BMI (2)	Youngpoong	Sungho				
MEQ (1)						Volvo Korea
ELE (2)		Sebang battery		LG electronics		LG electronics

Among the seven sectors, every sector has more than two innovators, while the MEQ sector only has one (Volvo Korea/2016 to 2017). As this sector also shows the lowest environmental productivity, it requires more innovator firms to lead it. Looking at each firm, SPL (FOD), Wooryong (MNM), and LG electronics (ELE) were registered twice as innovators during the sample period, implying that these three firms could be the core role models for firms in their respective sectors. For instance, LG electronics has produced energy efficient refrigerators since 2013. Owing to this effort, they have exported these refrigerators to India and obtained 173,000 tons of accumulated Certificated Emissions Reduction from United Nations Framework Convention on Climate Change (UNFCCC), 62,000 tons in India, which can be sold on the Korean ETS market. This is regarded as one of LG Electronics' most outstanding performances as an innovator. If we look at the 2015–2016 period, only SPL registered as an innovator. However, there were four innovator firms the following year, implying that the drastic increase in the SML happened because of the efforts of these firms.

5. Conclusions

As a developing country becoming an advanced economy, Korea has emphasized rapid economic development. However, there have been serious air pollution disasters nationwide, and thus, it is urgent for the Korean government to find workable, environmentally–friendly economic policies. This research analyzed the feasibility of the Korean government's environmental policies by focusing on the ETS. The main findings from the empirical tests can be summarized as follows.

The entire Korean manufacturing industry showed a very small upward trend in its average SML value (0.3%) over the sample period. Furthermore, the post-2015 results were very encouraging, showing a higher upward trend (0.8%). This means that environmental regulation has obviously been enhancing environmental performance with positive signals within 3 years, supporting the Porter hypothesis. Unfortunately, nonetheless, the regulations have not enhanced environmental efficiency by much, and thus, the Korean government should strengthen its regulatory policies to maintain and strengthen this upward trend to make the national emission target achievable or feasible.

We examined not only the entire manufacturing industry's performance, but also the environmental performance of each sector. According to the results, FOD, MNM, and ELE showed positive results, with averages more than 1, while the remaining four sectors did not. CHE and BMI showed drastic upward trends in 2017, which makes it possible to expect positive future results. We also found that capital- and energy-intensive sectors such as ELE showed good performance after 2015. They contribute the major share of GHG emissions; this means that regulations have shown a good effect already. However, the MEQ sector did not show a value more than 1 for the entire seven years; thus, both internal efforts for learning from benchmark firms and external public support to promote innovative activities are required to enhance its environmental performance in hardware-oriented facilities such as the machinery and transportation sectors.

By decomposing the SML index, it is also possible to identify the major driving factor that influences environmental productivity. In this study, the EC average was below one, while the TC average was the opposite, implying that the innovation effect is the main driver for environmental productivity. Therefore, each inefficient firm should engage in self-learning from benchmarking to enhance efficiency through innovation. Meanwhile, although we assumed that the TC average is higher than one, the pattern of each sector was different. Therefore, comparatively lower sectors such as MEQ should be more innovative to maintain their overall environmental productivity. From the TC index value and efficiencies of consecutive years, we could obtain group innovators for each sector. These innovator firms are good models for benchmarking with respect to productivity and innovation, and other firms may enhance their environmental performance by learning from the group innovators' cases. This might be the easiest solution for the urgent need to enhance the EC value.

Since the Korean government hosted the Green Climate Fund in Incheon, it has made great efforts to enhance its environmentally-friendly growth. Nonetheless, the research shows that unilateral measures such as the ETS may have problems, and thus, more precisely differentiated environmental regulation for each industry are required. Moreover, the research results support the idea that green technology innovation is a key factor for promoting growth in the green economy. The benchmarking firms definitely play a leading role in promoting innovation activities, and thus, more performance-oriented incentives for these leading firms could result in a trickle-down effect in green technology. Although this study has several implications, it still has some limitations. First, as the non-parametric approach used in this study does not offer statistical reliability, it might be necessary to use the bootstrapping approach. Second, the Meta-frontier approach may provide a more in-depth analysis in considering heterogeneity across diverse sectors.

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