FORUM

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EVALUATING THE FEASIBILITY AND EFFICIENCY OF KOREA'S ENVIRONMENTAL POLICIES FOR CARBON NEUTRALITY IN THE MANUFACTURING SECTOR

Avaliação da viabilidade e da eficiência das políticas ambientais da Coreia para a neutralidade de carbono no setor manufatureiro

Evaluación de la viabilidad y eficiencia de las políticas ambientales de Corea para la neutralidad de carbono en el sector manufacturero

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ABSTRACT

The Korean government has promoted regulatory policies for carbon neutrality by 2050. As an export-driven country with a high reliance on the manufacturing industry, Korea faces significant challenges in achieving its national reduction targets. This study examines the total factor carbon efficiency (TFCE) of the Korean manufacturing industry to develop feasible solutions. We employed the metafrontier sequential slack-based model (M-SSBM) to reflect the group heterogeneity arising from industrial characteristics. Data from 35 subsectors were collected from 2012 to 2019, and these subsectors were classified into three groups: technology, capital, and labor-intensive. The average TFCE of all industries shows a downtrend. Meanwhile, the TFCE of the three groups commonly showed good performance in the group-frontier, while it resulted in different group rankings in the metafrontier. A panel Tobit regression was conducted in the second stage, and the result shows that exports are significantly related to enhancing TFCE.

Keywords*: manufacturing industry, emission trading scheme, sequential SBM model, metafrontier DEA, total factor carbon efficiency.*

RESUMO

O governo coreano promoveu políticas regulatórias para alcançar a neutralidade na emissão de carbono até 2050. Sendo um país orientado para as exportações e altamente dependente da indústria transformadora, a Coreia enfrenta desafios significativos para alcançar as suas metas nacionais de redução. Este estudo examina o fator total de eficiência de carbono (FTEC) da indústria manufatureira coreana para desenvolver soluções viáveis. Para tanto, empregamos o modelo baseado em folga sequencial metafronteira (M-SSBM) para refletir a heterogeneidade do grupo decorrente das características industriais. Dados de 35 subsetores foram coletados de 2012 a 2019, e esses subsetores foram classificados em três grupos: tecnologia, capital e trabalho intensivo. O FTEC médio de todas as indústrias mostra uma tendência de baixa. Enquanto isso, o FTEC dos três grupos em conjunto mostrou bom desempenho na fronteira de grupo, ao mesmo tempo que resultou em diferentes classificações de grupo na metafronteira. Para obter implicações, foi realizada uma regressão Tobit em painel na segunda fase, e o resultado mostra que as exportações estão significativamente relacionadas com o aumento do FTEC.

Palavras-chave*: indústria manufatureira, esquema de comércio de emissões, sequential SBM model, metafrontier DEA, eficiência de carbono do fator total.*

RESUMEN

El gobierno coreano ha promovido políticas regulatorias para la neutralidad de carbono para 2050. Como país impulsado por las exportaciones con una gran dependencia de la industria manufacturera, Corea enfrenta desafíos importantes para lograr sus objetivos nacionales de reducción. Este estudio examina el factor total de eficiencia del carbono (FTEC) de la industria manufacturera coreana para desarrollar soluciones factibles. Para ello, empleamos el modelo basado en holgura secuencial de metafrontera (M-SSBM) para reflejar la heterogeneidad del grupo que surge de las características industriales. Se recopilaron datos de 35 subsectores entre 2012 y 2019, y estos subsectores se clasificaron en tres grupos: tecnología, capital e intensivos en mano de obra. El FTEC promedio de todas las industrias muestra una tendencia a la baja. Mientras que el FTEC de los tres grupos conjuntamente mostró un buen desempeño en la frontera del grupo, al mismo tiempo que resultó en diferentes clasificaciones grupales en la metafrontera. Para obtener implicaciones, se realizó una regresión Tobit en panel en la segunda etapa y el resultado muestra que las exportaciones están significativamente relacionadas con la mejora del FTEC.

Palabras clave: *industria manufacturera, esquema de comercio de emisiones, sequential SBM model, metafrontier DEA, factor total de eficiencia del carbono.*

INTRODUCTION

Global warming is one of the most critical challenges to a sustainable planet today. This phenomenon has resulted from a gradual rise in the Earth's average surface temperature caused by an increase in greenhouse gas (GHG) emissions. The effects of global warming are widespread, including rising sea levels, more frequent and severe weather disasters, and biodiversity loss. Nowadays, many countries are experiencing the climate crisis and its resulting catastrophes, and there are continuous media reports of various property damage and unpredictable loss of life due to climate change worldwide.

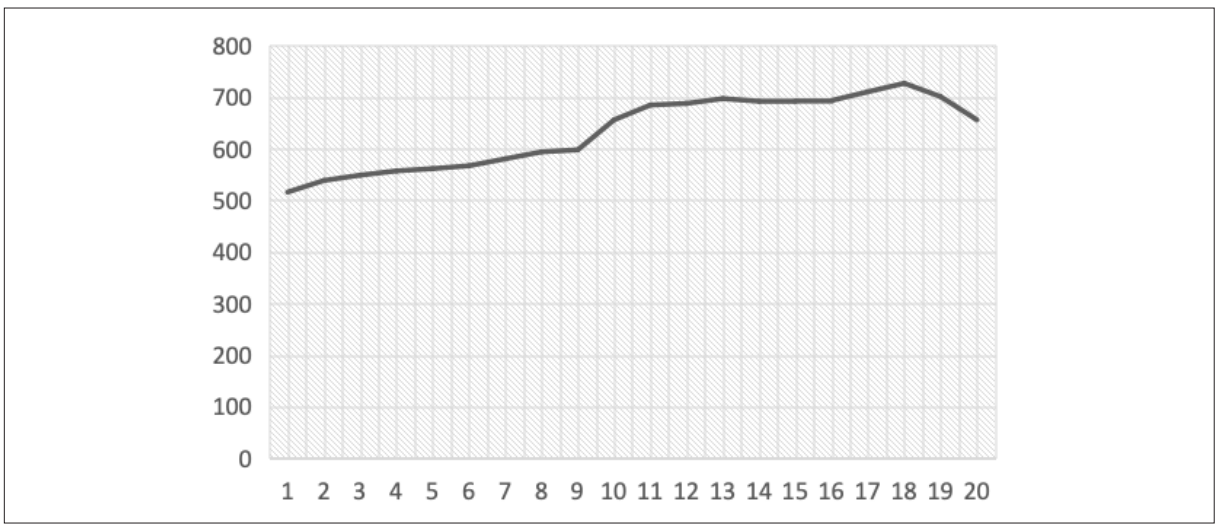
The Sixth Assessment Report of the United Nations (UN) Intergovernmental Panel on Climate Change (IPCC) affirmed that these frequent and extreme changes are attributable to human activities. The more specific cause of climate change is the rapid increase *in the global population and the production and use of products that result in the massive consumption of resources and fossil fuels (coal, oil, natural gas, etc.). Of the approximately 60 billion tons of GHG emitted worldwide, about 19 billion tons accumulate in the atmosphere yearly without being absorbed by the oceans or forests. As a result, the average concentration of* CO2 is about 415ppm (Bhatti et al., 2024), which is 149% higher than the average concentration before industrialization in 1750. The latest report from the IPCC has warned that the global average temperature will likely increase by 1.5 degrees Celsius by 2040, representing the target set by the international community in the 2015 Paris Climate Change Accord to combat global warming. The increase from 2011 to 2020 is significant, considering that the global surface temperature has already risen by 1.1 degrees compared to the average temperature between 1850 and 1900. If the temperature continues to rise, it will cause a wider range of abnormal weather patterns and have a detrimental effect on socio-economic aspects such as food security and life expectancy. Hence, the IPCC has emphasized the urgent need to achieve net-zero GHG emissions, including carbon dioxide, to limit global warming. To respond to the climate crisis, countries around the world have formulated GHG reduction targets of 23 gigatons (Gt.) from 65 Gt. of business as usual (BAU) to 42 Gt. by 2030 (KEEI report).

As of 2022, Korea's GHG emissions are about 601 million tons, ranking 10th globally. In addition, its emissions account for 1.67% of the world's emissions and are higher than those of the UK (318 million tons) and France (297 million tons) (ClimateWatch data). Of these emissions, the manufacturing sector produces a significant share at approximately 380 million tons, representing 57.9% of the total emissions in Korea. This paper defines governance as the workable mechanism for sustainable performance. There are lots of regulatory or promotional policies to reduce carbon emissions. Thus, diverse policies promote green technology innovation and/or business strategies to change its optimal path toward a carbon-neutral economy. Nonetheless, due to the lack of governance, most policies just perform superficial short-term effects, failing to achieve sustainable long-term efficiency. In particular, according to the National Greenhouse Gas Inventory Management System, GHG emissions in

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South Korea consistently increased throughout the 2000s and 2010s, with a slight decrease in 2019 (see Fig.1). As can be seen in Figure 1, even though the Korean government has promoted the Emission Trading Scheme (ETS) since 2015, it has not shown any declining trend except during the COVID-19 pandemic, implying that the Korean government's regulatory policy on GHGs and carbon emissions has not worked well. Furthermore, it means that there are very high policy risks associated with emissions abatement, resulting in a lack of governance. While many countries, such as Korea, have determined the optimal path to control carbon emissions, in reality, their performance has been poor with ever-increasing emissions, as is shown in the case of Korea in Figure 1.

Figure 1. Trend of GHGs in South Korea



Note: www.gir.go.k

In line with the global trend, the Yoon government in South Korea has recently launched the First Carbon Neutral Green Normal Plan, which aims to reduce the country's GHG emissions and promote sustainable economic development (Kim et al., 2022). As part of this plan, the government has set a Nationally Determined Contribution (NDC) for 2030, intending to reduce GHG emissions to 436.6 million tons from 727.6 million tons in 2018. The ultimate goal is to achieve carbon neutrality by 2050. Nonetheless, according to a recent report by the Korean Ministry of Environment, since the peak of GHG emissions in 2018, the total amount of GHG emissions in Korea is decreasing, but the GHG emissions of the manufacturing sector are increasing (Yang & Ahn, 2023). Given this poor performance in the manufacturing industry, unfortunately, the Korean government has modified its abatement strategy to have much less of a burden on the manufacturing sector from 222.6 million tons (14.5%) to 230.7 million tons (11.4%), a 3.1% lowered reduction target, while the energy sector will assume this higher portion through the increased support of nuclear power generation. Because Korea has an export-oriented economy, the Korean government should listen to the claims of the manufacturing sector's leading groups regarding the potential cost burden of carbon emission abatement. Ultimately,

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is this new environmental policy really feasible and efficient for the sustainable development of the Korean economy?

The answer lies in a missing link in terms of a lack of governance. In particular, the current lack of effective governance hinders the implementation of government policies, especially in terms of achieving the sustained performance of the manufacturing sector. As a country that relies heavily on the manufacturing industry, which accounts for 27.9% of its gross domestic production (GDP), South Korea faces significant challenges in achieving its national GHG reduction targets. Therefore, the manufacturing industry should reduce its carbon emissions; however, for various reasons, performance differs widely from one sector to another. For example, Samsung and POSCO are two leading companies in Korea, accounting for 8% and 3.7% of the country's GDP, respectively, and contributing 27.7% and 12.4% of the country's export volume. Put briefly, these companies are considered the backbone of the Korean economy. However, regarding the CO2 emissions policy, the two companies have taken different paths. Despite the increase in the total CO2 emissions of both companies, POSCO's emissions, on a per 100 million won sales basis, have decreased while Samsung's emissions have increased. What caused this divergence? Was it due to inherent industry factors or the organizations' cultural characteristics, or was it the result of government policy?

To answer these questions more effectively, examining environmental efficiency in the manufacturing industry from the perspective of a 'total factor' framework is required. Therefore, this study examines the TFCE (Total factor carbon efficiency) of 35 manufacturing industries in Korea over the years 2012–2019. This result may have significant implications for Korea's low-carbon economy. In addition, using Panel Tobit analyses, we aim to identify governance factors that have contributed to improving the TFCE in economic activities.

The contributions of this study can be summarized as follows. First, we used aggregated industry data, which includes almost all firms in Korea. Because most previous papers have merely examined parts of these industries on the firm level with limited data, there is some bias in terms of the political effect on the whole economy. This research fills this gap in the literature by performing an integrated evaluation of all manufacturing firm data. Second, this research includes a wide range of data across industries, causing a heterogeneity issue. However, to solve the bias arising from this difference across industries, a metafrontier approach is introduced to fill the gap in terms of the diverse characters of the industries. Additionally, by adopting sequential DEA, which is an appropriate way to reflect the nature of technology, we confirm whether overestimation occurs when normal DEA is employed. Third, to determine the effect of governance factors on TFCE, we conducted panel Tobit regression, which enabled us to provide strategic implications and suggestions.

The remainder of this paper is organized as follows: The next section presents the literature review, and the subsequent section presents the methodology. The penultimate section introduces the descriptive data and the empirical results and discusses them. The final section summarizes policy implications and concludes the study.

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LITERATURE REVIEW

Literature on environmental efficiency based on the DEA approach

The popular Data Envelopment Analysis (DEA) model was pioneered by Farrell (1957) and has been widely used in the Energy & Environment field. However, its application in academia was limited due to certain measurement flaws. After Charnes et al. (1978) proposed the CCR model, Banker et al. (1984) came up with the idea of assuming the existence of "returns to scale." However, ignoring slack variables in traditional DEA models, which take a radial approach, could result in overestimation and inaccuracy. Therefore, the slack-based model DEA (Tone, 2001) was proposed. The SBM-DEA method comprehensively captures inefficiencies in input and output factors (Chang, 2013; Chen et al., 2017; Choi et al., 2020). Its straightforward definition of production technology ensures that it provides more dependable and pertinent insights and recommendations, making it a preferred approach for efficiency assessment. However, although the SBM-DEA seems to be appropriate for this study, Shestalova (2003) pointed out a limitation in this standard approach: the production frontier may move inward, implying a "technological regression." This assumption is not suitable for exploring the manufacturing sector in that the productivity decline may be temporary, and technological regression may be misleading. Therefore, Shestalova (2003) adopted the concept of sequential DEA to examine 11 OECD countries' environmental productivity. Because of the advantages of sequential DEA, numerous studies (Choi & Wang, 2017; Lee & Choi, 2019; Oh & Heshmati, 2010; Shestalova, 2003; Xie & Wang, 2015; Yu et al., 2017; Zhang & Kim, 2014) have applied it to explore environmental performance. Hence, we adopt a sequential slack-based measure (SSBM) to obtain TFCE in this study. Table 1 presents the research in the E&E field in terms of the application of DEA.

Table 1. Literature on the Application of DEA

Author(s)	Subject	Measurement	Methodology	Variables
Matsumoto et al. (2020)	EU countries (2000–2017)	Environmental performance	DEA	Input–labor, capital, energy; desirable output–GDP; undesirable output–CO_2, PM2.5 and, waste
Woo et al. (2015)	31 OECD countries (2004–2011)	Environmental efficiency	DEA	Input–labor, capital, renewable energy supply; desirable output–GDP; undesirable output–CO_2
Wei et al. (2021)	Chinese transportation 2017	Environmental and energy efficiency	DEA	Input–labor, fixed assets investment, energy consumption; desirable output–passenger turnover, freight turnover, and value-added; undesirable output–CO_2

Continue

Table 1. Literature on the Application of DEA

Concludes

Author(s)	Subject	Measurement	Methodology	Variables
Chen et al. (2017)	Regional industry in China (2008–2012)	Environmental efficiency	SBM-DEA	Input–labor, energy, investment in fixed assets of industry; desirable output–GDP; undesirable output–total emissions of sulfur dioxide and industrial solid waste
Choi et al. (2020)	China regional (2011–2017)	Atmospheric efficiency	SBM-DEA	Input–labor, capital, energy; desirable output–GRDP; undesirable output–SO_2, NOx, PMs
Chang (2013)	Ports in Korea 2010	Environmental efficiency	SBM-DEA	Input–labor, capital, energy; desirable output–cargo tonnage and vessel tonnage; undesirable output–CO_2
Shestalova (2003)	11 OECD countries (1970–1990)	Productivity performance	Sequential DEA	Input–labor, capital, energy; desirable output–GDP; undesirable output–CO_2, PM2.5 and waste
Oh & Heshmati (2010)	26 OECD countries (1970–2003)	Environmentally sensitive productivity growth	SML	Input–labor, capital, energy; desirable output–GDP; undesirable output–CO_2, PM2.5 and waste
Yu et al. (2017)	Coal-fired Chinese power plant (1999–2008)	Carbon productivity growth	SMLPI	Input–labor, capital, energy; desirable output–GDP; undesirable output–CO_2, PM2.5 and waste
Xie & Wang (2015)	270 cities of China (2003–2012)	Land use efficiency	SSBM	Input–land, capital, labor; desirable output–the value added; undesirable output–SO2, wastewater, soot
Zhang & Kim (2014)	Korean power companies (2007–2011)	Energy efficiency	SSBM	Input–labor, capital, energy; desirable output–GDP; undesirable output–CO_2, PM2.5 and waste
Choi & Wang (2017)	Korean 16 local governments (2006–2013)	Land use efficiency	SSBM	Input–labor, capital, energy; desirable output–GDP; undesirable output–CO_2, PM2.5 and waste
Lee & Choi (2019)	Korean manufacturing industry (2011–2013)	Environmental performance	SGDDF	Input–labor, capital, energy; desirable output–sales turnover; undesirable output–GHG

Note: EU = European Union; DEA = data envelope analysis; SBM-DEA = slack-based measure data envelopment analysis; GDP = gross domestic product; OECD = Organization for Economic Cooperation and Development; SML = sequential Malmquist–Luenberger; SMLPI = sequential metafrontier Luenberger productivity index; SSBM = sequential slack-based measure; SGDDF = sequential generalized directional distance function.

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Literature review of metafrontier DEA approach

In the previous section, we introduced the concept of DEA along with the model we selected. However, this study aims to assess the environmental TFCE and also reflect the sectoral heterogeneity across industries. Generally, each industry shows a different pattern regarding its financial value or carbon intensity. Therefore, if we assume that the production technologies of DMU are similar or identical, we may overlook the heterogeneity between different sub departments, which may lead to inaccurate performance evaluation. Estimation bias may also occur when calculating efficiency (Long et al., 2018). Therefore, we adopt a metafrontier approach.

The metafrontier approach has been widely used when considering regional (Wang et al., 2013; Wang et al., 2017; Yu et al., 2019; Zhang et al., 2015) and sectoral heterogeneity (Chen et al., 2017; Lee, 2021; Qin et al., 2020; Yang et al., 2020; Zou et al., 2022). When the research subject is a region, the economic level of the specific region is the main reason. On the other hand, for sectoral studies, especially regarding the manufacturing industry, an obvious sectoral heterogeneity difference exists that arises from economic scale, technical level, carbon intensity, and so on. Because the Korean manufacturing industry also shows an obvious difference, we adopt the concept of metafrontier DEA and compare the contemporaneous DEA results in this study. Table 2 presents several studies that adopt metafrontier DEA.

Table 2. Literature on the Application of Metafrontier DEA

Author(s)	Subject	Measurement	Group classification	Variables
Zhang et al. (2015)	Ecological total-factor energy efficiency in China (2001–2010)	MSBM	Region	Input–labor, capital, energy; desirable output–GDP; undesirable output–CO_2, SO_2, COD
Yu et al. (2019)	China's eco-efficiency (2003–2015)	Meta-U-SBM, Meta-U-EBM, and Meta-U-MinDW	Region	Input–labor, capital, energy, land usage; desirable output–GDP; undesirable output–PI (pollution index)
Wang et al. (2017)	China provincial energy efficiency (2000–2014)	Metafrontier	Region	Input–energy, capital, labor; desirable output–GDP; undesirable output–CO_2
Wang et al. (2013)	Energy efficiency and production technology hetero in China (2000–2010)	Metafrontier DEA	Region	Input–energy, capital, labor; desirable output–GDP
Lee (2021)	Korean manufacturing industry (2012–2017)	Metafrontier Malmquist–Luenberger	Industry	Input–labor, capital, energy; desirable output–sales revenue; undesirable output–CO_2

Continue

Table 2. Literature on the Application of Metafrontier DEA Concludes

Author(s)	Subject	Measurement	Group classification	Variables
Chen et al. (2017)	New energy vehicle industry in China (2012–2019)	Three-hierarchy metafrontier	Industry	Input–number of technical employees, R&D expenditure; link Input–patents, number of manufacturing employees, number of marketing employees, market expenditure; output–net profit
Zou et al. (2022)	High-tech industry in China (1999–2018)	Metafrontier DEA	Industry	Input–R&D capital: 10,000 CNY, R&D personnel: persons; output–patent applications: pieces, sales revenue of new products: 10,000 CNY
Qin et al. (2020)	Thermal power plants in China (2006–2015)	Metafrontier non-radial slacks-based measure	Industry	Input–labor, capital, energy; desirable output–thermal power generation Undesirable output–CO_2, SO_2
Yang et al. (2020)	Manufacturing industry in China (2003–2015)	Metafrontier DEA	Industry	Input–labor, capital, energy; output–economic output, CO_2

Note: MSBM = metafrontier slack-based efficiency measure; DEA = data envelope analysis; GDP = gross domestic product.

METHODOLOGY

This section presents the SSBM employed to evaluate the TFCE of each subsector. In the next subsection, we present the metafrontier approach (M-SSBM) to identify heterogeneity issues among each group. In the subsequent subsection, we introduce the Panel Tobit regression model, which was employed to identify the determinant factors of TFCE.

Sequential SBM-DEA with undesirable output

Based on previous research, our model also assumes that manufacturing industries use three inputs: energy consumption (E), labor (L), and capital (K), respectively, to generate sales revenue (T) and CO2 emissions (C). This production technology can be illustrated as:

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

P is typically assumed to satisfy the standard axiom of production theory (Färe & Grosskopf, 2006). For example, inactivity is always possible, and finite amounts of input can produce only finite outputs. In addition, inputs and desirable outputs are often assumed to be strongly or freely disposable.

Drawing from the insights of Tulkens and Eeckaut (1995), the sequential technology is illustrated as follows:

S.T,

$$(y^g, y^b)\ x \text{ produce } (y^g, y^b) \qquad (2)$$

$$x \geq \sum_{r=1}^{t} \sum_{n=1}^{N} \lambda_n^r x_{nm}^r$$

$$y^g \leq \sum_{r=1}^{t} \sum_{n=1}^{N} \lambda_n^r \ y_{ns1}^{gr}$$

$$y^b \geq \sum_{r=1}^{t} \sum_{n=1}^{N} \lambda_n^r y_{ns2}^{br}; \lambda \geq 0$$

Equation (2) is generally estimated separately for each time t; this is often translated into wide oscillations. We used sequential technology, implying that the estimation of (2) is conducted each time, which includes not only the current year but also all the years preceding it. Meanwhile, production technology will change over time. Therefore, we imposed the constraints of the variable returns to scale (VRS) on the objective function. Hence, the optimization problem of sequential SBM (SSBM) takes the following form.

$$\theta_{SBM}^{k^*} = min \frac{1}{1 + \frac{1}{s+p}(\sum_{r=1}^{s} \frac{s_r}{y_r} + \sum_{k=1}^{p} \frac{s_k}{b_k})}$$

S.T,

$$\sum_{r=1}^{T} \sum_{n=1}^{N} \lambda_n^r x_{nm}^r + s_i$$

$$\sum_{r=1}^{T} \sum_{n=1}^{N} \lambda_n^r y_{ns}^{gr} - s_r$$

$$\sum_{r=1}^{T} \sum_{n=1}^{N} \lambda_n^r y_{np}^{br} + s_k$$

$$s_i, s_r, s_k \geq 0, \lambda \geq 0 \qquad (3)$$

m=1,2,…,m, number of inputs
s=1,2,…,m, number of good outputs
p=1,2,…,m, number of bad outputs
r= 1,2,…, s_r, index of good outputs
k= 1,2,…, s_k, index of bad outputs
s_i slack variables (potential reduction) of inputs
s_r slack variables (potential enhancement) of good outputs
s_k slack variables (potential enhancement) of bad outputs
λ a non-negative multiplier vector for the production possibility set construction using linear programming.

Equation (2) defines a non-radial, output-oriented measurement of the SSBM model. When $\theta^{k*}_{SBM} = 1$, this implies that all slack variables are 0, implying that the specific subsector's TFCE is efficient.

Metafrontier sequential SBM-DEA and its decomposition

Generally, the effciency level obtained from different production frontiers cannot be compared because of heterogeneity issues. For instance, such heterogeneity could exist on the economic level, or the carbon intensity heterogeneity of production could be different. Considering this issue, the concept of metafrontier originated from Hayami (1969) and Hayami and Ruttan (1970). In research, the metaproduction function can be regarded as the envelope of commonly conceived neoclassical production functions (Hayami & Ruttan, 1970). O'Donnell et al. (2008) also mentioned that the input–output structure could be different among countries, regions, and industries.

By combining the SSBM model (3) and metafrontier technology, we present the M-SSBM. The M-SSBM can be examined by solving the following equation.

$$\theta^{k*}_{SBM} = min \frac{1}{1 + \frac{1}{s+p}\left(\sum_{r=1}^{s}\frac{s_r}{y_r} + \sum_{k=1}^{p}\frac{s_k}{b_k}\right)}$$

S.T. (4)

$$s.t. \sum_{r=1}^{T}\sum_{h=1}^{H}\sum_{n=1}^{N_h}\lambda_n^h x_{nm}^t + s_i$$

$$\sum_{r=1}^{T}\sum_{h=1}^{H}\sum_{n=1}^{N_h}\lambda_n^h y_{ns1}^t - s_r$$

$$\sum_{r=1}^{T}\sum_{h=1}^{H}\sum_{n=1}^{N_h}\lambda_n^h b_{ns2}^t + s_k$$

$$\sum_{h=1}^{H}\sum_{n=1}^{N_h}\lambda_n^h = 1$$

$$s_i, s_r, s_k \geq 0, \lambda \geq 0$$

Meanwhile, as shown by O'Donnell et al. (2008), TFCE under metafrontier technologies could be classified into within-group TFCE and the meta-technology ratio (MTR). Within-group TFCE measures the relative efficiency of observations under specific group frontier technologies. Meanwhile, MTR, implying the technology gap ratio, captures the proximity of a group frontier technology to a metafrontier technology. If the MTR value is higher, it means the group frontier technology approaches the metafrontier technology. Thus, when MTR is 1, there is no gap between these two technologies. Following O'Donnell et al. (2008), we also decomposed the Meta TFCE (MTFCE) into a Group TFCE (GTFCE) and an MTR index as follows:

$$\text{MTFCE} = \text{GTFCE} \times \text{MTR} \tag{5}$$

Panel Tobit regression model

When the efficiency value is used as a dependent variable in a regression model, we may face the fact that the values are restricted to a range. (For our research, the eco-efficiency scores had many maximum thresholds with a value of 1, meaning that the data were right truncated.) Because Tobit regression can handle the limited dependent variable with maximum likelihood estimation (MLE), to determine the governance factor of the TFCE for each subsector, we adopted the Panel Tobit regression (Lee, 1979), which can be illustrated as Equation (6):

$$Y_{it}^{*} = X_{it}\beta + \mu_i + \varepsilon_{it}, Y_{it} = Y_{it}^{*}, \text{ if } Y_{it}^{*} > 0, Y_{it} = 0 \tag{6}$$

DATA AND GROUP CLASSIFICATION

Data and variables

To examine the TFCE, we obtained data from 35 sub-industries from the period 2012 to 2019. Because of data scarcity, we limited the period to 8 years for the empirical study. The industries were classified using the method provided by the United Nations Standard International Trade Classification (SITC), as shown in Table 3.

Table 3. Subsectors of Korean Manufacturing Industry

Technology-intensive	Capital-intensive	Labor-intensive
Petrochemistry	Oil refining	Food and beverage
Fine chemistry	Rubber	Tobacco
General purpose machinery, special machinery	Plastic, glass	Textile, apparel

Continue

Table 3. Subsectors of Korean Manufacturing Industry Concludes

Technology-intensive	Capital-intensive	Labor-intensive
Car	Ceramic	Leather and shoes
Railway	Cement	Wood
Transportation etc.	Non-metallic mineral	
Pharmaceutical	Iron and steel	
Semiconductor	Nonferrous	
Computer, communication device	Casting of metals	
Precision instrument	Fabricated metal	
Battery, shipbuilding, aviation	Furniture, paper making, printing	

Source: ISTANS (https://istans.or.kr/mainMenu.do)

Table 4 presents descriptive data - capital, labor, and sales revenue. These three variables were obtained from the Industrial Statistics Analysis System (ISTANS). Moreover, energy consumption and CO2 emissions were collected from the Korean Statistical Information Service (KOSIS).

Table 4. Statistics

Variable	Type	Unit	*M*	*SD*	Max.	Min.
Revenue	Desirable output	Korean Won (million)	38,250,251	43,525,705	201,018,142	961,654
CO_2	Undesirable output	CO_2–equivalent tons	8,319	20,363	123,202	28
Capital	Input	Korean Won million)	15,192,567	17,450,704	87,989,739	502,193
Labor	Input	Per person	71,849	77,737	347,821	1,951
Energy	Input	Toe	3,343	8,618	37,686	6

Note: ISTANS (https://istans.or.kr/mainMenu.do) and KOSIS (http://kosis.kr/index/index.do).

Determinants of carbon efficiency

Building on the literature, we evaluate the feasibility of four major determinants (Zit) of TFCE for industrial subsectors; R&D investment per capita, export dependency, market concentration, and foreign direct investment (FDI).

Market concentration (MC): MC refers to the degree of competitive power in the market. To maintain its MC, an industry subsector makes more efforts to enhance its efficiency. In this study, the degree of MC is the number of firms that belong to a specific subsector.

Export dependency (EX): EX refers to how much a specific subsector depends on exports—in this study, the share of export value per total industrial output value.

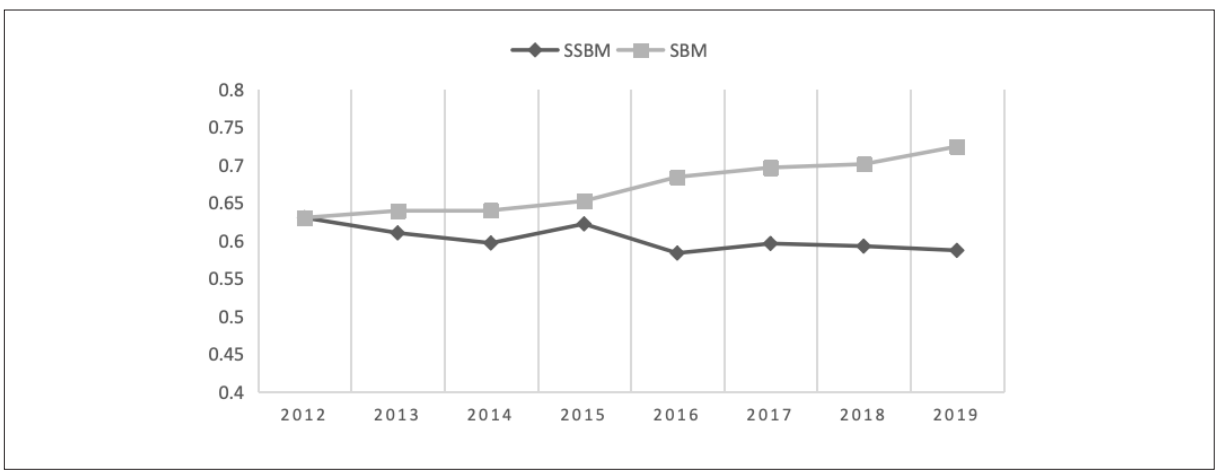
R&D per capita (RD): RD refers to the quantitative efforts toward progressing technology, which is an important factor for productivity growth. In this study, we used the R&D investment amount per researcher of a specific subsector.

FDI: FDI refers to the outbound economies of scope in terms of advanced technology and management experience. A company may invest in a foreign country if it can learn any green technology related to this FDI; thus, a higher FDI results in better opportunities to enhance efficiency via the spillover effect of advanced technology and management skills. In this paper, we used the FDI value of a specific subsector.

EMPIRICAL RESULTS

Before analyzing the empirical results obtained with SSBM, it is necessary to check the feasibility of all variables when adopting the model selection. To clarify the empirical difference between SSBM and normal SBM, we examined the SBM results with the same data and determined that both results show not only a different average value but also a different trend over time. The average TFCE of both approaches is shown in Figure 2. As shown in the figure, the gap between the two different measures in terms of efficiency enlarges over time, resulting in an overshooting effect of the policies. This implies that SBM could overestimate efficiency, resulting in a biased policy impact. Moreover, SSBM shows a more delicate change between its peak and foot in the figure, implying that SSBM is more accurate and precise in presenting the up and down of efficiency. Therefore, SSBM is the more appropriate and precise approach for evaluating the performance of policies, especially in the manufacturing industry.

Figure 2. Comparison between SSBM and SBM



Group-frontier efficiency

Using the better measure of SSBM, we first obtained group-frontier TFCE values (see Table 5). We found that the three groups showed a comparatively higher average value than 0.7 during the study period. The labor-intensive group had the best group-frontier TFCE performance with an average of 0.8, and the capital-intensive group also showed a relatively high value, while the technology-intensive group showed the lowest value. Because the efficiency within a group shows a similar relative difference within the same group, the companies in the labor-intensive group, such as those in the food or textile industries, may demonstrate a similar performance, implying a relatively higher average efficiency. Contrary to the labor-intensive group, the companies in the technology-intensive group, such as those in the pharmaceutical and computer industries, may have more divergent amounts of CO2 emissions and a much lower performance overall, led by air-polluting industries such as the precision-instrument subsector, which increased from 0.399 in 2014 up to 0.480 in 2019. Correspondingly, the intra-industry difference in performance seems much worse in the technology-intensive group.

Moreover, in terms of the total average value, a downtrend is visible during this empirical period, implying that ongoing mechanisms such as ETS or Target management system (TMS) have not positively influenced TFCE improvement. Even if the government outlined the predictable path of environmentally friendly emission regulatory policies, business practices have not aligned with this direction. Therefore, to determine which sectors had better performance, we evaluated inter-industry differences by calculating the metafrontier efficiency.

Table 5. Group-frontier TFCE by Sector

Sector	2012	2013	2014	2015	2016	2017	2018	2019
Technology-intensive	0.727	0.725	0.707	0.765	0.703	0.726	0.718	0.704
Pharmaceutical	0.548	0.539	0.536	0.553	0.521	0.523	0.511	0.526
Semiconductor	0.624	0.638	0.655	1.000	0.681	1.000	1.000	0.877
Computer	0.701	0.755	0.718	0.782	0.773	0.877	0.938	0.891
Communication device	1.000	1.000	0.877	1.000	0.873	0.866	0.806	0.789
Precision instrument	0.399	0.391	0.382	0.422	0.440	0.479	0.481	0.480
Battery	0.612	0.586	0.538	0.607	0.574	0.601	0.635	0.658
Aviation	0.527	0.575	0.611	0.791	0.688	0.487	0.518	0.529
Petrochemistry	1.000	1.000	0.919	0.923	0.798	0.835	0.867	0.807
Fine chemistry	0.560	0.554	0.551	0.554	0.567	0.560	0.567	0.562
General purpose machinery	0.650	0.628	0.624	0.626	0.607	0.628	0.640	0.653

Continue

Table 5. Group-frontier TFCE by Sector

Concludes

Sector	2012	2013	2014	2015	2016	2017	2018	2019
Special machinery	0.590	0.597	0.606	0.624	0.616	0.688	0.673	0.660
Car	1.000	1.000	1.000	1.000	0.942	0.962	0.914	0.947
Railway	1.000	0.929	0.893	0.900	0.804	0.810	0.692	0.641
Shipbuilding	0.699	0.683	0.688	0.691	0.654	0.580	0.523	0.544
Transportation etc.	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Capital-intensive	0.864	0.844	0.821	0.818	0.779	0.804	0.807	0.818
Oil refining	1.000	1.000	0.955	0.771	0.703	0.787	0.893	0.874
Rubber	0.869	0.834	0.808	0.784	0.746	0.746	0.737	0.733
Plastic	0.912	0.902	0.890	1.000	0.900	0.933	0.884	0.953
Glass	0.718	0.664	0.617	0.610	0.595	0.580	0.583	0.584
Ceramic	1.000	1.000	0.914	1.000	0.810	0.912	1.000	1.000
Cement	0.917	0.939	0.914	0.940	0.978	0.960	0.995	0.873
Non-metallic mineral	1.000	0.902	0.891	0.844	0.940	1.000	0.823	0.876
Iron and steel	0.675	0.650	0.620	0.593	0.573	0.613	0.612	0.609
Nonferrous	1.000	0.952	0.919	0.908	0.870	0.918	0.918	0.927
Casting of metals	0.754	0.737	0.722	0.711	0.710	0.720	0.731	0.760
Fabricated metal	1.000	0.953	1.000	1.000	0.955	0.936	0.878	0.971
Paper making	0.609	0.617	0.610	0.629	0.630	0.622	0.654	0.661
Printing	0.650	0.674	0.630	0.664	0.603	0.590	0.591	0.634
Furniture	1.000	1.000	1.000	1.000	0.897	0.932	1.000	1.000
Labor-intensive	0.870	0.878	0.849	0.842	0.828	0.827	0.787	0.798
Food and beverage	1.000	1.000	1.000	1.000	0.941	1.000	1.000	1.000
Tobacco	1.000	1.000	1.000	1.000	1.000	0.978	0.934	0.856
Textile	0.680	0.728	0.659	0.638	0.618	0.637	0.635	0.653
Apparel	1.000	1.000	1.000	1.000	0.831	0.755	0.766	0.877
Leather and shoes	1.000	1.000	0.868	0.821	1.000	1.000	0.800	0.817
Wood	0.542	0.541	0.566	0.591	0.579	0.591	0.589	0.586

Note: Values in the technology-intensive, capital-intensive, and labor-intensive rows reflect the group-wide average per year.

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Metafrontier efficiency

After obtaining the group-frontier TFCE, we examined the metafrontier TFCE, as shown in Table 6. Overall, the total average shows a downtrend similar to that of the group-frontier TFCE; this implies a lack of governance regarding the regulatory policies on carbon emissions.

However, if we review the respective inter-group results, we find some unique implications in terms of the differentiation of regulatory policies. Although it is a timid change, the labor-intensive group shows a downtrend, the capital-intensive group shows a U-trend, and the technology-intensive group shows a fluctuating trend. Moreover, the ranking of these three groups' average TFCE values differs from that of group-frontier TFCE values, and it is noteworthy that the group differences are wide. The capital-intensive industry could be characterized as an engine for economic growth that has been leading the Korean economy. Nonetheless, its average TFCE is less than 0.5, implying that the capital-intensive industry has much more potential for improvement. However, the Korean government has recently alleviated industrial emission targets since front-line industrial representatives have expressed difficulty reaching them. In this case, the TFCE will deteriorate more as time goes by, and the net-zero goal will be more difficult to achieve.

Regarding specific subsectors, the tobacco, car, and transportation industries have a very high TFCE, while the glass, ceramic, non-metallic mineral, and printing industries show the lowest TFCE. For instance, the car industry shows the highest values for both the group and meta TFCE. The good performance of the car industry in terms of carbon emissions may be due to the competitive pressure in the global market. In particular, the car industry is currently facing severe competition in the global market. Therefore, it is regarded that increasing the pressure to achieve environmental efficiency to create a "sustainable image" in the global market also leads to higher efficiency in the local market. Here, we can guess that "global market pressure" is crucial for a company to conduct environmentally friendly business. Meanwhile, the cement industry shows a higher group TFCE and a much lower meta TFCE, as shown in Figure 3. As the cement industry is obviously a heavy emitter, even if it decreases its emissions significantly, considering the relative scale of its reduction by comparing with the metafrontier may result in overestimated efficiency. Therefore, the Korean government should consider group characteristics in its target distribution.

Table 6. Metafrontier TFCE by Sector

Sector	2012	2013	2014	2015	2016	2017	2018	2019
Technology-intensive	0.708	0.686	0.691	0.749	0.691	0.714	0.706	0.694
Pharmaceutical	0.536	0.526	0.525	0.544	0.513	0.517	0.507	0.523
Semiconductor	0.624	0.638	0.655	1.000	0.681	1.000	1.000	0.877
Computer	0.701	0.755	0.718	0.782	0.773	0.877	0.938	0.891
Communication device	1.000	1.000	0.877	1.000	0.873	0.866	0.806	0.789
Precision instrument	0.399	0.391	0.382	0.422	0.440	0.479	0.481	0.480
Battery	0.565	0.539	0.501	0.581	0.545	0.576	0.617	0.645

Continue

Table 6. Metafrontier TFCE by Sector

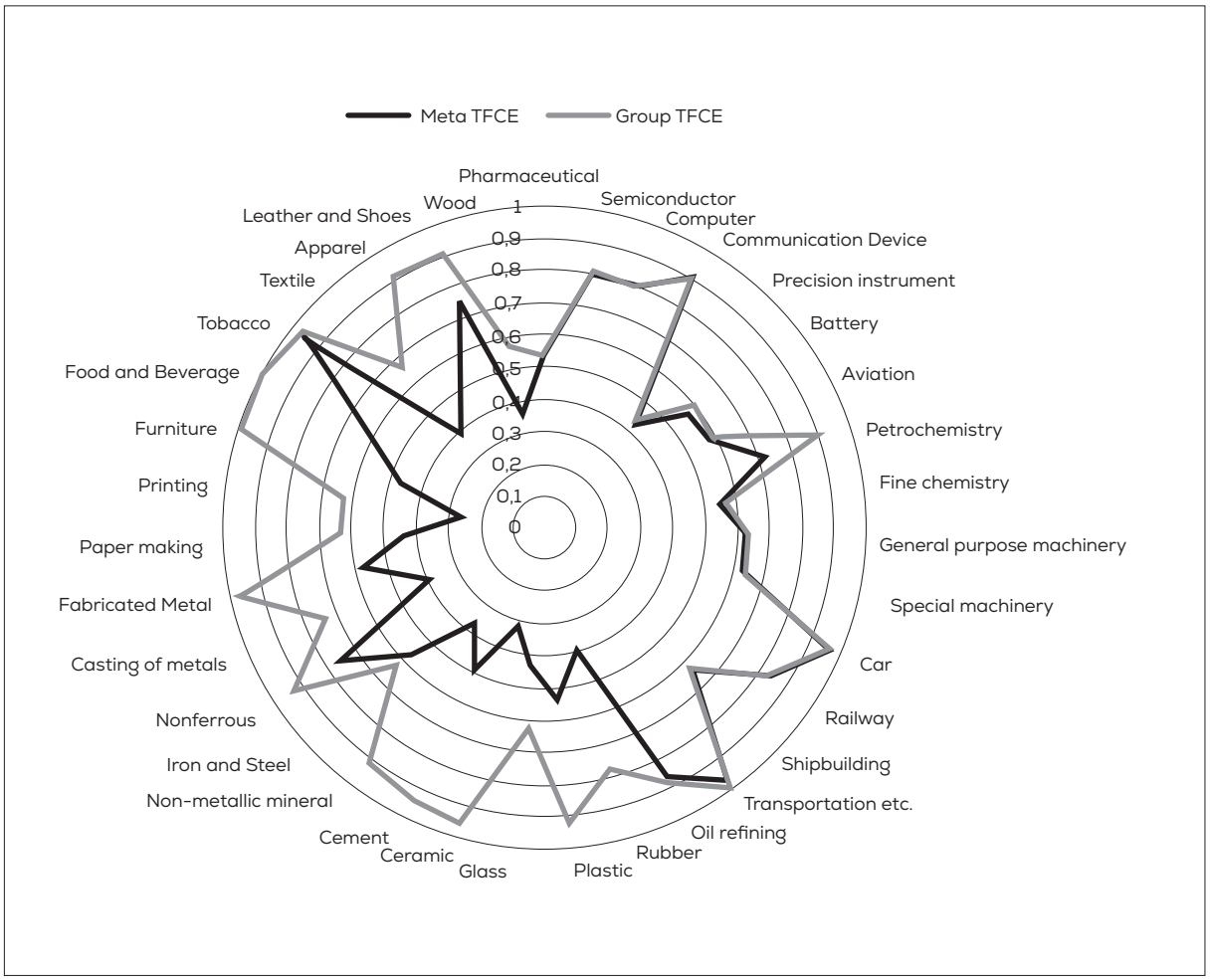
Concludes

Sector	2012	2013	2014	2015	2016	2017	2018	2019
Aviation	0.524	0.575	0.611	0.791	0.688	0.486	0.508	0.515
Petrochemistry	0.778	0.758	0.740	0.753	0.655	0.689	0.718	0.678
Fine chemistry	0.558	0.551	0.550	0.528	0.567	0.560	0.567	0.562
General purpose machinery	0.650	0.628	0.624	0.626	0.607	0.628	0.640	0.653
Special machinery	0.590	0.597	0.606	0.624	0.616	0.688	0.673	0.660
Car	1.000	1.000	1.000	1.000	0.942	0.962	0.914	0.947
Railway	1.000	0.929	0.893	0.900	0.804	0.810	0.692	0.641
Shipbuilding	0.699	0.683	0.688	0.691	0.654	0.580	0.523	0.544
Transportation etc.	1.000	0.721	1.000	1.000	1.000	1.000	1.000	1.000
Capital-intensive	0.538	0.514	0.496	0.490	0.464	0.475	0.483	0.485
Oil refining	1.000	1.000	0.948	0.771	0.703	0.787	0.892	0.873
Rubber	0.421	0.411	0.409	0.417	0.388	0.382	0.380	0.390
Plastic	0.523	0.532	0.539	0.569	0.538	0.543	0.531	0.548
Glass	0.476	0.442	0.425	0.415	0.414	0.404	0.403	0.396
Ceramic	0.353	0.342	0.315	0.371	0.298	0.304	0.312	0.303
Cement	0.493	0.505	0.503	0.515	0.513	0.516	0.499	0.489
Non-metallic mineral	0.389	0.378	0.359	0.360	0.354	0.366	0.371	0.367
Iron and steel	0.627	0.598	0.578	0.549	0.527	0.568	0.575	0.572
Nonferrous	1.000	0.787	0.722	0.707	0.696	0.720	0.724	0.726
Casting of metals	0.413	0.390	0.381	0.380	0.365	0.367	0.373	0.382
Fabricated metal	0.628	0.603	0.598	0.605	0.579	0.576	0.554	0.579
Paper making	0.443	0.435	0.427	0.431	0.421	0.428	0.441	0.439
Printing	0.284	0.285	0.269	0.280	0.266	0.251	0.258	0.259
Furniture	0.488	0.492	0.474	0.492	0.433	0.437	0.449	0.462
Labor-intensive	0.627	0.623	0.578	0.595	0.572	0.563	0.550	0.546
Food and beverage	0.643	0.645	0.642	0.661	0.637	0.644	0.639	0.668
Tobacco	1.000	1.000	1.000	1.000	1.000	0.945	0.908	0.807
Textile	0.400	0.408	0.392	0.394	0.375	0.378	0.379	0.377
Apparel	0.525	0.483	0.541	0.614	0.487	0.460	0.447	0.474
Leather and shoes	1.000	1.000	0.646	0.630	0.712	0.701	0.656	0.665
Wood	0.336	0.333	0.355	0.374	0.359	0.371	0.372	0.369
Total	0.630	0.610	0.597	0.622	0.584	0.596	0.593	0.587

Note: Values in the technology-intensive, capital-intensive, and labor-intensive rows reflect the groupwide average per year.

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Figure 3. Comparison between Meta TFCE and Group TFCE (Average)



MTR

Regarding the MTR index results, the technology-intensive group shows the highest average MTR value (0.98) across the empirical period, followed by the labor-intensive and capital-intensive groups with the lowest average values. This result implies that the technology-intensive group shows the smallest technological gap to the metafrontier technology. As we saw from the metafrontier TFCE results, the other two groups show much lower MTR, which means that both groups are far from the metafrontier technology compared to the technology-intensive group. Because the MTR index represents the gap between the group-frontier and the metafrontier, to bridge this gap, we need to find policy support on the governance factors that will enhance TFCE. Thus, we applied Panel Tobit regression, as discussed in the following section.

Table 7. MTR

Sector	2012	2013	2014	2015	2016	2017	2018	2019
Technology-intensive	0.978	0.958	0.981	0.981	0.984	0.985	0.985	0.986
Pharmaceutical	0.977	0.976	0.979	0.983	0.986	0.989	0.992	0.994
Semiconductor	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Computer	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Communication device	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Precision instrument	1.000	1.000	0.999	1.000	1.000	1.000	1.000	1.000
Battery	0.923	0.921	0.931	0.958	0.948	0.957	0.972	0.980
Aviation	0.994	0.999	1.000	1.000	1.000	0.998	0.982	0.974
Petrochemistry	0.778	0.758	0.804	0.816	0.820	0.825	0.828	0.840
Fine chemistry	0.995	0.995	0.997	0.953	1.000	1.000	1.000	1.000
General purpose machinery	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Special machinery	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Car	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Railway	1.000	1.000	1.000	1.000	0.999	1.000	1.000	1.000
Shipbuilding	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Transportation etc.	1.000	0.721	1.000	1.000	1.000	1.000	1.000	1.000
Capital-intensive	0.626	0.613	0.610	0.612	0.608	0.603	0.607	0.602
Oil refining	1.000	1.000	0.992	1.000	1.000	1.000	0.999	0.999
Rubber	0.485	0.493	0.506	0.531	0.520	0.512	0.516	0.532
Plastic	0.574	0.590	0.606	0.569	0.598	0.582	0.601	0.575
Glass	0.663	0.665	0.689	0.681	0.696	0.697	0.691	0.678

Continue

Table 7. MTR

Concludes

Sector	2012	2013	2014	2015	2016	2017	2018	2019
Ceramic	0.353	0.342	0.345	0.371	0.367	0.334	0.312	0.303
Cement	0.538	0.538	0.550	0.548	0.525	0.538	0.502	0.559
Non-metallic mineral	0.389	0.420	0.402	0.427	0.377	0.366	0.451	0.419
Iron and steel	0.928	0.920	0.932	0.925	0.920	0.927	0.939	0.939
Nonferrous	1.000	0.827	0.786	0.780	0.800	0.784	0.789	0.783
Casting of metals	0.547	0.530	0.528	0.534	0.514	0.510	0.511	0.502
Fabricated metal	0.628	0.633	0.598	0.605	0.606	0.616	0.631	0.597
Paper making	0.728	0.705	0.699	0.685	0.669	0.689	0.675	0.665
Printing	0.438	0.422	0.426	0.422	0.441	0.426	0.437	0.409
Furniture	0.488	0.492	0.474	0.492	0.483	0.469	0.449	0.462
Labor-intensive	0.729	0.717	0.691	0.715	0.701	0.691	0.707	0.695
Food and beverage	0.643	0.645	0.642	0.661	0.677	0.644	0.639	0.668
Tobacco	1.000	1.000	1.000	1.000	1.000	0.967	0.972	0.943
Textile	0.588	0.560	0.594	0.617	0.607	0.594	0.596	0.577
Apparel	0.525	0.483	0.541	0.614	0.587	0.609	0.583	0.540
Leather and shoes	1.000	1.000	0.744	0.767	0.712	0.701	0.820	0.814
Wood	0.620	0.616	0.626	0.632	0.620	0.628	0.631	0.630
Total	0.794	0.779	0.783	0.788	0.785	0.782	0.786	0.782

Note: Values in the technology-intensive, capital-intensive, and labor-intensive rows reflect the groupwide average per year.

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Panel Tobit regression

Using the metafrontier TFCE as the dependent variable, we attempted to identify the influential governance factors on TFCE. As mentioned above, we selected four factors and conducted Panel Tobit regression. Table 8 shows the results of the Tobit regression.

Table 8. Panel Tobit Regression Results

Variable	Panel Tobit	
	Coefficient	*t*
MC	2.33	0.19
EX	6.11***	9.64
RD	0.14	0.88
FDI	-2.78**	-2.3
_cons	0.49***	12.63

Note: MC = market concentration; EX = export dependency; RD = R&D per capita; FDI = foreign direct investment. ***, **, and * represent the significance level of 1%, 5%, and 10%, respectively. C is a constant term.

Market concentration (MC)

As seen in Table 8, the positive role of MC is rejected with a low statistical significance, which implies that market pressure in the domestic market is insufficient to incentivize a company to make more efforts to reduce its emissions level. Therefore, to boost the positive role of MC, the government should create much stronger regulations for emissions reductions. Otherwise, a company may confuse the ultimate goal of carbon zero with the current practices of loosening emission abatement targets for the manufacturing industry.

Export dependency (EX)

In contrast to MC, which represents domestic competitive pressure, export dependency (EX) indicates the global market pressure on carbon emissions abatement. Contrary to the negligible effect of MC, EX showed a statistically significant result and a much higher effect on emissions reductions with its outstanding positive coefficient of 6.11, implying a much higher influence on energy efficiency. Moreover, this result suggests that new and emerging international trade norms, such as carbon border adjustment mechanisms (CBAM), influence export-oriented companies to make more efforts to enhance their TFCE. Given Korea's export-oriented economic structure,

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low-carbon production seems essential for most Korean companies to be able to improve exports in the future, which demonstrates that promoting policies on emissions abatement for exporting companies is strongly recommended in light of the new carbon-zero global norm.

R&D per capita (RD)

Although numerous studies have reported that R&D investment positively influences energy efficiency, this research did not find a statistically significant result regarding this relationship. This may stem from the fact that even if Korean companies focus on technological innovation through R&D investment, their share of green R&D is negligible. Green technology covers a diverse spectrum from an investment or cost perspective. For low-cost green technology, the government should create much stronger regulations to pressure companies to be satisfied with the performance of these low-cost green technologies. On the other hand, the government should create more incentive-oriented promotion policies for high-cost (or investment) green technology because regulation is not appropriate for encouraging a company to assume such a high-risk, high-return project.

FDI

Foreign direct investment showed a negative relationship with TFCE, which contradicts our hypothesis, implying that more FDI going out results in aggravated emissions related to this FDI. Most leading Korean companies may have great challenges in reducing carbon emissions. To avoid this trade-off between its production growth without decreasing its emissions under the home country's regulations, it should transfer its facilities to other countries through FDI, resulting in much worse emissions with fewer production facilities.

CONCLUSION

This paper evaluated a TFCE of Korean manufacturing industries using a sequential SBM-DEA. Because this approach can reflect the heterogeneity resulting from the different performances by group, it is appropriate for examining manufacturing industry subsectors, which have diverse industrial characteristics. Ultimately, the main findings of the study can be summarized as follows.

First, the group-frontier TFCE shows a high average value overall, while the metafrontier is much lower, implying a significant intra-group spill-over effect. In particular, the capital-intensive group shows the lowest metafrontier TFCE value, implying a much lower performance than other inter-industry levels. This may stem from the market-oriented

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Emission Trading Scheme (ETS), which has somewhat controlled environmental performance through this group of high-emitter sectors. Within the capital-intensive group, a company may not be very aware of regulatory policies due to the certain perceived safety coming from the categorical indifference within the group. Regarding specific subsectors, the tobacco, car, and transportation industries show very high TFCE values, while the glass, ceramic, non-metallic mineral, and printing industries show relatively low values. Therefore, the government should not put any invisible wall around the different groups. Thus, the car manufacturing industry could enhance much higher efficiency gain if, and only if, the company can learn from other group practices.

Second, the technology-intensive group shows the highest average MTR value at 0.9 across the empirical period. The labor-intensive group had the second highest value, and the capital-intensive group had the lowest average value. This finding implies that the technology-intensive group shows the smallest technological gap to the metafrontier technology, while the other two groups are far from the metafrontier technology. Further, it suggests that differentiated policies are required for companies within the other two groups for the learning effect not from the same group but from others.

Third, according to our Panel Tobit regression results, export dependency shows an outstanding governance effect on the performance of emissions reductions due to the positive influence on TFCE. Interestingly, FDI shows a negative relationship with TFCE, which implies that restructuring the FDI between the home country and the host country is not beneficial for the Korean economy.

The Korean government has promoted inbound FDI to improve technology and higher global standards for carbon emissions, but it was not found in our research. Instead, the export dependency of the company strongly promoted carbon emission reduction, implying that the government should put more regulatory policies on the global companies in Korea and better incentives for the companies to increase export volume. This means that market-oriented policies are more effective than government-led promotions, which are shown in promotional FDI. In summary, the heterogeneity or divergence of the carbon emission efficiency does come from the outside rather than the internal market, implying that the government should reduce any subjective categorizing on the group differential for their reduction targets because higher efficiency of one company may come from the artificial categorized government policies such as the lower regulation on inbound FDI companies.

Although this study offers several contributions, there are still limitations. First, because we adopted a non-parametric measure, which shows a statistical limitation, bootstrapping or stochastic models are recommended to ensure statistical reliability. Second, because the ETS is an ongoing environmental mechanism, it is important to examine the shadow price to evaluate the feasibility of the market-based ETS. Third, because the ETS applies to companies with more than 600 firms, analyzing data from firms participating in ETS will provide unique implications.

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NOTES

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CONFLICTS OF INTEREST

The authors have no conflicts of interest to declare.

AUTHORS' CONTRIBUTION

Hyongsuk Lee: Data curation; Formal analysis; funding acquisition; Methodology; Software; Writing – original draft; Writing – proofreading, and editing.
Yongrok Choi: Conceptualization; funding acquisition; Project administration; Supervision; Writing – original draft; Writing – proofreading, and editing.
Hojin Jeong: Conceptualization; Data curation; Investigation; Resources; Validation; Visualization; Writing – original draft
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