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Research article

Measuring performance of supply chains based on data envelopment analysis and multi-regional input-output analysis: An application to 18 manufacturing sectors in 43 countries

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ABSTRACT

This study developed a novel framework that combined data envelopment analysis and multi–regional input–output database to investigate the economic and environmental productivity change in the global supply chains associated with 18 manufacturing sectors in 43 countries from 2000 to 2014. Two models are developed; manufacturer model is used to evaluate performance of direct production activity of a sector in countries and supplier model is used to evaluate performance of indirect production activity of upstream suppliers of the sector. The proposed framework enables us to separately analyze the performance of supply chains into direct production activity and indirect production activity of suppliers. The empirical results show that the environmental productivity of direct production activity of 18 manufacturing sectors was improved by 12.9 percent, while the environmental productivity of the upstream suppliers was improved by only 4.7 percent during 2000–2014 on average. Different patterns of economic and environmental productivity growth were observed between the direct production activity and upstream suppliers in all sectors. The finding suggests that the performance of an entire supply chain should be separately analyzed to consider industry-specific policies. The proposed framework is used to identify countries that succeed/fail to improve economic and environmental performance. Based on the results, this study discusses policies regarding production and supply chain management toward CO_2 mitigation.

1. Introduction

In recent years, numerous countries have made considerable efforts towards mitigating the climate change problem. In 2015, 196 Parties at 21st Conference of the Parties adopted the Paris Agreement, which aims to limit global warming to well below 2 °C compared to the preindustrial level [1]. Most of the Parties submitted Intended Nationally Determined Contributions, in which greenhouse gas (GHG) emission reduction targets were set. For example, the European Union and its member states are committed to a binding target of a domestic reduction of at least 40% in GHG emissions by 2030 compared to 1990 [2]. CO_2 accounts for 65% of the total GHG emissions [3]. Global CO_2 emissions have considerably increased since 1900, and the global CO_2 emissions from fuel combustion were 33.5 billion tons in 2018 [4]. The industrial sector is the largest CO_2 emitter; it accounted for approximately 43% CO_2 emissions after reallocating electricity and heat in 2018 [4].

Therefore, countries need to improve production technology and reduce CO_2 emissions from fuel combustion and electricity and

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heat consumption in the industrial sector for climate change mitigation [5]. In addition to emission reduction efforts at the production stage, green supply chain management has attracted the attention of policy- and decision-makers worldwide [6–8]. As globalization progresses and supply chain structures become more complex, green supply chain management becomes a key element for reducing CO_2 emissions in an entire supply chain, and the importance of measuring the environmental performance of supply chains has been emphasized [9,10].

Many studies have analyzed the energy and environmental performance at production stage in manufacturing sector to discuss CO_2 reduction policy [11–14]. Honma and Hu [11] investigated industry-level total-factor energy efficiency in 14 developed countries; they focused on Japan and identified benchmark countries for inefficient Japanese manufacturing industries. Lu et al. [14] assessed environmental energy efficiency of 48 high-income countries from 2010 to 2014; they showed that countries with higher energy efficiency have large energy consumption, and it is difficult for those countries to reduce CO_2 emissions through energy efficiency improvement.

Although these studies analyzed cross-country energy and environmental efficiency, their efficiency evaluation was based on input-output data used directly by industries and countries. For example, Honma and Hu [11] used industrial capital stock, labor force, and energy and material consumptions as input data and industrial value added as desirable output data. They evaluated the energy efficiency of industrial sectors of 14 countries based on the input-output data. Lu et al. [14] used capital stock, energy consumption, and labor force as input data, GDP as desirable output data, and CO_2 emissions as undesirable output data. They evaluated the environmental efficiency of 48 countries based on the input-output data.

Even though an industrial sector in a country reduces its direct energy consumption or direct CO_2 emissions from its production activity, if indirect energy consumption and emissions from upstream suppliers of the sector increase, then total emissions from the entire supply chain of the sector could increase. A developed country may outsource its upstream production activities to other cheap-labor countries to reduce costs, reducing direct emissions of the developed country. Thus, considering indirect input and emissions provides new insights into performance measurement. However, it is challenging to measure the performance of supply chains owing to the lack of standardized methodologies [10].

In the context of efficiency and productivity analysis, some researchers combined frontier-based approach and environmentally-extended multi-regional input-output (EEMRIO) analysis to consider performance of supply chains [5,15,16]. Takayabu et al. [5] combined data envelopment analysis (DEA) and EEMRIO analysis to estimate scope 1, 2, and 3 emission reduction potentials through productive efficiency improvement in 14 metal sectors of 40 countries. Although they considered both direct and indirect CO_2 emissions, their research framework is unable to consider the environmental performance of upstream production activities. Wang et al. [15] combined DEA and EEMRIO analysis to measure the environmental performance of supply chains of manufacturing sectors in 16 economies. They first used EEMRIO analysis to estimate embodied input-output data associated with supply chains of manufacturing sectors. Then, they evaluated the environmental performance of entire supply chains of manufacturing sectors. The proposed model enables us to measure the environmental performance of supply chains; however, it is difficult to distinguish the performance of production activity and supply chain management.

Two types of production activities are involved in supply chains: direct production activity and upstream production activity. Direct production activity involves the actual creation and assembly of products. Upstream production activity refers to producing goods and services that serve as intermediate inputs or raw materials for the direct production activity. Accounting input-output data of direct and upstream production activities separately provides insights to discuss improving the environmental performance of supply chains. Input-output data of direct production activity helps us to review the performance of production activity of a specific industrial sector of a country. Input-output data of upstream production activity helps us to review the green supply chain management of a specific industrial sector of a country.

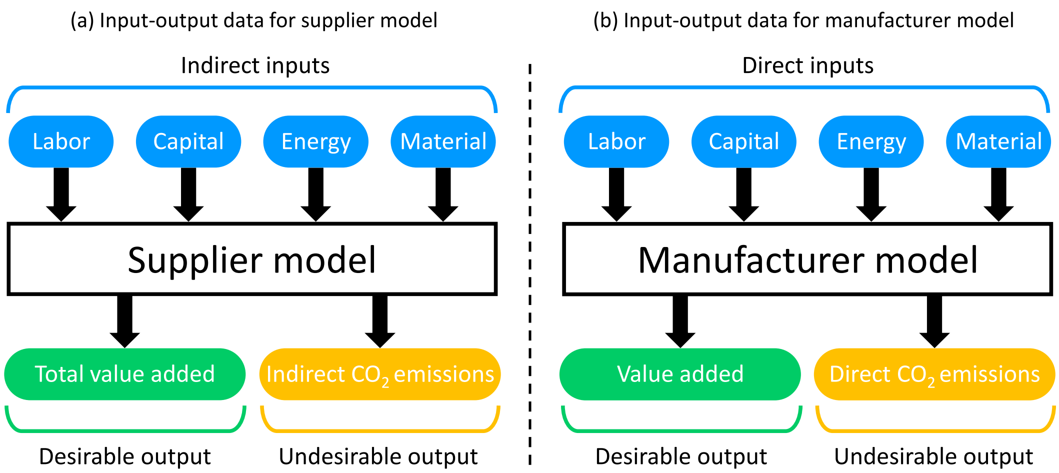

Fig. 1. Research models developed in this study.

With this background, this study develops a research framework that aims to separately measure the performance of direct and upstream production activities of manufacturing sectors in different countries. Specifically, this study uses an EEMRIO table to construct a sector-level dataset of inputs and desirable and undesirable outputs. Then, DEA is applied to the input-output dataset to measure the performance of supply chains. Two models are developed; one is the manufacturer model that focuses on the direct production activity of a country's sector (Fig. 1(b)), and the other is the supplier model that focuses on the indirect production activity of upstream suppliers of the sector (Fig. 1(a)). Thus, the manufacturer model is used to evaluate the performance of the production technology of a sector, and the supplier model is used to evaluate the performance of the supplier network of the sector. Compared with the conventional model used to evaluate the performance of "entire" supply chains (e.g., Refs. [15,16]), the developed framework is novel in that it can "separately" analyze the performance of direct production activity of a sector and indirect production activity by upstream suppliers of the sector.

An empirical analysis using the developed framework is performed; specifically, the World Input–Output Database (WIOD, [17,18]) is used to construct a dataset of four inputs (labor, capital, energy, and material), one desirable output (value added), and one undesirable output (CO_2 emissions) for 18 manufacturing sectors in 43 countries from 2000 to 2014. Table 1 presents the classification of the 18 manufacturing sectors. Then, the Global–Malmquist Luenberger (GML) productivity index (Oh [19]) is utilized to measure the economic and environmental productivity change in the supply chains of each sector and country. The results obtained by the proposed model and a conventional model are compared. Furthermore, policies regarding production and supply chain management toward CO_2 mitigation in manufacturing sectors are discussed.

2. Literature review

2.1. *Cross-country efficiency and productivity studies*

Frontier-based approaches, such as stochastic frontier analysis (SFA) and data envelopment analysis (DEA) are widely used to measure efficiency and productivity in different countries. SFA is a parametric approach that can deal with statistical noise, and it requires the pre-assumption of a functional form of an efficient frontier [20]. On the contrary, DEA is a nonparametric approach, and it does not require a functional assumption [20]. DEA is preferred for cross-country efficiency and productivity analysis owing to its nonparametric features [21].

This section reviews 72 studies that used DEA to evaluate economic and environmental efficiency in different countries. Table A1 (Appendix A) provides information on the decision-making unit (DMU), sectoral data (if applied), study period, returns to scale (RTS), DEA projection, inputs, desirable outputs, and undesirable outputs of each study. This study selects three inputs (labor, capital, and energy), two desirable outputs (GDP and value added), and four undesirable outputs (CO_2, SO_x, NO_x, and GHG emissions) as representative production factors in cross-country DEA studies.

Amowine et al. [22] applied DEA to 25 African countries during 2007 and 2014. Their DEA model considered three inputs (capital, labor, and energy), one desirable output (GDP), and one undesirable output (CO_2). Most of the studies used country-level data, and only nine studies used industrial or sectoral data. For example, Arcelus and Arocena [23] used the sector-level data of the manufacturing industry and service industry in 14 OECD countries and analyzed the total factor productivity of each industry and country.

The assumption of returns to scale is also presented in Table A1. DEA was originally developed by Charnes et al. [24], who constructed an efficient production frontier under a constant returns to scale (CRS) assumption. Banker et al. [25] extends the CRS model to a variable returns to scale (VRS) model. The scale efficiency of DMUs was estimated using the CRS and VRS models (Banker et al. [25]). According to Table A1, 47 and 17 studies adopted the CRS and VRS assumptions, respectively. In addition, 8 studies applied both assumptions to analyze scale efficiency.

Table A1 also describes the DEA projection of each study. In general, DEA models are divided into two types (radial and nonradial projection models) according to the method used to measure the distance between an observation and efficient production frontier. Radial and nonradial projection models aim to obtain the maximum rate of input contraction (or output expansion) with the same proportion and different proportions, respectively [26]. Radial models include those developed by Charnes et al. (1978), Banker et al. [25], Chambers et al. [27], and Chung et al. [28], and nonradial models include those proposed by Färe and Lovell [29], Charnes et al. [30], Cooper et al. [31], and Tone [32]. The comparisons between radial and nonradial models are summarized in Avkiran et al. [26]. As shown in Table A1, 52 studies used radial models, 19 studies used nonradial models, and one study used both models.

Regarding the production factors, 53 studies considered undesirable outputs to study environmental efficiency in different countries, whereas the others did not consider undesirable outputs. Among the 72 studies, 57, 60, and 48 studies considered capital, labor, and energy as input factors, respectively. In addition, 59 and 7 studies used GDP and value added as desirable output factors, respectively, and 42, 9, 7, and 9 studies considered CO_2, SO_x, NO_x, and GHG emissions as undesirable output factors, respectively.

Sector-level efficiency analysis is preferred over country-level analysis because it can deal with the heterogeneity that exists among different countries. Efficiency studies with country-level data could be biased when heterogeneity exists among different countries (i.e., when countries have different industrial structures, the results of efficiency analysis could be unrealistic). Conversely, efficiency studies with sector-level data can provide more appropriate results and implications to discuss environmental policies. However, only few studies used sector-level data owing to data availability. Cross-country analysis via DEA could be biased when such heterogeneity exists (Takayabu [33]). In addition, sector-level analysis provides more detailed and practical results when discussing efficiency improvement policies. Therefore, this study uses sector-level data and focuses on 18 manufacturing sectors that play an important role in climate change mitigation. It constructs an $18 \times 43 \times 15$ panel dataset consisting of 18 manufacturing sectors in 43 countries from

Table 1
Sector classification.

Category	ID	ISIC code	Sector name in WIOD	Number of DMUs
Labor intensive sectors	L.1	C10–C12	Manufacture of food products, beverages and tobacco products	43
	L.2	C13–C15	Manufacture of textiles, wearing apparel and leather products	43
	L.3	C16	Manufacture of wood and of products of wood and cork, except furniture; Manufacture of articles of straw and plaiting materials	35
	L.4	C17	Manufacture of paper and paper products	37
	L.5	C18	Printing and reproduction of recorded media	36
	L.6	C31–C32	Manufacture of furniture; other manufacturing	43
Capital intensive sectors	C.1	C19	Manufacture of coke and refined petroleum products	38
	C.2	C20	Manufacture of chemicals and chemical products	39
	C.3	C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	39
	C.4	C22	Manufacture of rubber and plastic products	40
	C.5	C23	Manufacture of other non-metallic mineral products	34
	C.6	C24	Manufacture of basic metals	24
	C.7	C25	Manufacture of fabricated metal products, except machinery and equipment	40
Technology intensive sectors	T.1	C26	Manufacture of computer, electronic and optical products	40
	T.2	C27	Manufacture of electrical equipment	38
	T.3	C28	Manufacture of machinery and equipment n.e.c.	42
	T.4	C29	Manufacture of motor vehicles, trailers and semi-trailers	39
	T.5	C30	Manufacture of other transport equipment	38

Note: ISIC indicates international standard industrial classification, WIOD indicates world input-output database, and DMU indicate decision making unit.

2000 to 2014. Furthermore, this study adopts the CRS assumption and radial-type DEA model, which are used by the majority of the 72 studies. Specifically, the directional distance function (DDF) approach developed by Färe et al. [34] is used as the radial model. In addition, following the previous studies, this study considers four inputs (capital, labor, energy, and material input), one desirable output (value added), and one undesirable output (CO_2 emissions).

2.2. Environmental performance measurement of supply chains

Oliver and Webber [35] proposed the first definition of supply chain management. Since then, supply chain management has attracted the interest of economic and environmental policy and decision makers [7]. A large number of studies have measured the performance of supply chains through operational research (e.g., DEA, multicriteria decision making, and multiobjective mathematical programming) and life cycle assessment [6,7]. DEA is being increasingly used for measuring supply chain performance because it can construct a composite efficiency indicator from multiple inputs and outputs and identify peers with the best practice for benchmarking purposes [15,36]. Numerous models have been developed[1] for measuring supply chain performance. However, empirical studies are limited to the firm level and have a small sample size owing to data availability. Supply chains have complex structures, and it is difficult to obtain a comparable input–output dataset for DEA at the country or sector levels in a few cases.

A few researchers applied an input–output table to DEA and measured supply chain performance at the country or sector levels [5,11,15,33]. The input–output table covers a wide range of economic transactions between sectors and regions [42]. Egilmez et al. [43] proposed a combined economic input–output, life cycle assessment, and DEA (EIO-LCA-DEA) approach for the sustainability assessment of supply chains associated with 53 manufacturing sectors in the United States. The EIO-LCA-DEA approach can consider multiple input and output factors of entire supply chains, and it has been applied to other sectors and regions [44–47]. These studies are based on a single-region input–output table; thus, they perform cross-sector analysis within a country. In recent years, the EIO-LCA-DEA approach has been extended to cross-country analysis by applying a MRIO table [15,16,48].

Compared with conventional DEA applications, which considered only the direct input and output factors of DMUs, EIO-LCA-DEA studies successfully modeled direct and indirect input and output factors. Conventional DEA studies measured the performance of a production system, whereas EIO-LCA-DEA studies measured the performance of an entire supply chain system. This study further develops the supply chain performance measure with the MRIO table and DEA by dividing an entire supply chain system into a manufacturing phase and supplying phase.

The developed framework is described in Fig. 1. A supply chain is divided into direct production activity by a sector in a country and indirect production activity by upstream suppliers of the sector. Two models are developed and presented in the framework to measure the performance of supply chains in different countries. The manufacturer model considers the direct inputs, value added, and direct CO_2 emissions associated with production activity in a sector in different countries (Fig. 1(b)). In contrast, the supplier model considers the indirect inputs, total value added generated by upstream suppliers of the sector, and indirect CO_2 emissions associated with the upstream suppliers (Fig. 1(a)).

The developed framework has the following advantages: First, compared with the model used in EIO-LCA-DEA studies (hereinafter

[1] DEA models for supply chain performance measurement and their applications can be found in, e.g., Liang et al. [37], Castelli et al. [38]), Tone and Tsutsui [39], Chen and Yang [40], and Kao [36], and Badiezadeh [41].

referred to as the conventional model), the developed framework can divide the performance of an entire supply chain into manufacturer performance and supplier performance. Manufacturer performance is measured based on input and output data used in direct production activity of a sector of a country, whereas supplier is measured based on input and output data used indirect production activity of upstream suppliers of the sector. Second, the developed framework can identify the sources of inefficiency in an entire supply chain, hence the framework can separately analyze the performance of manufacturer and supplier. Thus, the obtained results can used for discussing policies regarding production and supply chain management toward CO_2 mitigation. For example, if the manufacturer performance in a sector in a country is low, the sector should focus on improving its production activity to reduce CO_2 emissions. On the contrary, if the supplier performance in a supply chain is low, the sector should reconsider its supply chain network and supplier selection through supply chain management.

3. Materials and methods

3.1. Constructing input–output dataset with global MRIO table

The input–output datasets for the manufacturer, supplier, and conventional models are constructed using the global MRIO table to measure performance of supply chains [42]. In the manufacturer model, the direct inputs of labor, capital, energy, and material are considered as the inputs, direct CO_2 emissions as the undesirable output, and the value added as the desirable output. In contrast, the supplier model considers the indirect inputs of labor, capital, energy, and material as the inputs, indirect CO_2 emissions as the undesirable output, and total value added generated by upstream suppliers as the desirable output. The conventional model (e.g., Ref. [15]) considers the sum of the inputs and outputs of the manufacturer and supplier models.

The structure of global EEMRIO database is shown in Fig. 2. Suppose that there are P countries and Q economic sectors. The total output of a sector in a country is consumed as either intermediate demand or final demand by all sectors in all countries. The equilibrium relationship can be formulated as

$$\mathbf{t} = \mathbf{Z1} + \mathbf{f} \tag{1}$$

where $\mathbf{t}$ and $\mathbf{f}$ are $PQ \times 1$ vectors that denote the total output and final demand, respectively. $\mathbf{Z}$ is a $PQ \times PQ$ matrix that denotes the intermediate demand matrix, and $\mathbf{1}$ is a $PQ \times 1$ vector for row sum Calculation. We define direct input coefficient matrix $\mathbf{A}$ as $\mathbf{A} = \mathbf{Z}\widehat{\mathbf{t}}^{-1}$, where $\hat{}$ indicates a diagonal matrix. Following the Leontief input–output model, Eq. (1) can be rewritten as

$$\mathbf{t} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{f} = \left(\mathbf{I} + \mathbf{A} + \mathbf{A}^2 + \cdots + \mathbf{A}^{\infty}\right)\mathbf{f} = \mathrm{L}\mathrm{f} \tag{2}$$

where $\mathbf{I}$ is an identity matrix, and $\mathbf{L}$ is the $PQ \times PQ$ Leontief inverse matrix.

The term $(\mathbf{I} + \mathbf{A} + \mathbf{A}^2 + \cdots + \mathbf{A}^{\infty})\mathbf{f}$ represents the interactive production activity within the global production network. For example, If indicates the direct production of final goods, and Af indicates the first-tier intermediate goods production required to produce the final goods. $\mathbf{A}^2\mathbf{f}$ indicates the second-tier intermediate goods production required to produce the first-tier intermediate goods. All production activities associated with the final demand are completely captured in Eq. (2) using interactions If, Af, $\mathbf{A}^2\mathbf{f}$, etc.

Eq. (2) can be combined with a $PQ \times 1$ energy coefficient vector, $\mathbf{e}$, and extended to calculate the direct and indirect energy inputs

Global MRIO table											
Input \ Output		Contry 1			⋯	Country P				Final demand	Total output
		Sector 1	⋯	Sector Q		Sector 1	⋯	Sector Q		
Country 1	Sector 1	$z_{11,11}$	⋯	$z_{11,1Q}$		$z_{11,P1}$	⋯	$z_{11,PQ}$	f_{11}	t_{11}
	⋮	⋮		⋮		⋮		⋮	⋮	⋮
	Sector Q	$z_{1Q,11}$	⋯	$z_{1Q,1Q}$		$z_{1Q,P1}$	⋯	$z_{1Q,PQ}$	f_{1Q}	t_{1Q}
⋮		⋮		⋮		⋮		⋮	⋮	⋮
Country P	Sector 1	$z_{P1,11}$	⋯	$z_{P1,1Q}$		$z_{P1,P1}$	⋯	$z_{P1,PQ}$	f_{P1}	t_{P1}
	⋮	⋮		⋮		⋮		⋮	⋮	⋮
	Sector Q	$z_{PQ,11}$	⋯	$z_{PQ,1Q}$		$z_{PQ,P1}$	⋯	$z_{PQ,PQ}$	f_{PQ}	t_{PQ}
Value added		v_{11}	⋯	v_{1Q}	⋯	v_{P1}	⋯	v_{PQ}		
Total input		t_{11}	⋯	t_{1Q}	⋯	t_{P1}	⋯	t_{PQ}		

SEA	
Capital	Labor
k_{11}	l_{11}
⋮	⋮
k_{1Q}	l_{1Q}
⋮	⋮
k_{P1}	l_{P1}
⋮	⋮
k_{PQ}	l_{PQ}

EA	
Energy	CO_2 emissions
e_{11}	c_{11}
⋮	⋮
e_{1Q}	c_{1Q}
⋮	⋮
e_{P1}	c_{P1}
⋮	⋮
e_{PQ}	c_{PQ}

Fig. 2. Structure of global EEMRIO database. Note: SEA: socio-economic account; EA: environmental account.

(i.e., embodied energy input) for the final demand of sector q in country p. $\bar{\mathbf{f}}_{pq}$ is defined as a $PQ \times 1$ vector whose pq element is the final demand of sector q in country p, and the other elements are zero. The embodied energy input for the final demand of sector q in country p can be formulated as

$$e_{pq} = \mathbf{e}^{\mathrm{T}}\mathbf{L}\bar{\mathbf{f}}_{pq} = \mathbf{e}^{\mathrm{T}}\mathbf{I}\bar{\mathbf{f}}_{pq} + \mathbf{e}^{\mathrm{T}}\left(\mathbf{A} + \mathbf{A}^2 + \cdots + \mathbf{A}^{\infty}\right)\bar{\mathbf{f}}_{pq} = \mathbf{e}^{\mathrm{T}}\mathbf{I}\bar{\mathbf{f}}_{pq} + \mathbf{e}^{\mathrm{T}}\mathrm{AL}\bar{\mathbf{f}}_{pq} \tag{3}$$

where T indicates a transposed matrix. Here, $\mathbf{e}^{\mathbf{T}}\mathbf{I}\bar{\mathbf{f}}_{pq}$ indicates the direct energy input required to produce the final demand of sector q in country p, and $\mathbf{e}^{\mathbf{T}}\mathrm{AL}\bar{\mathbf{f}}_{pq}$ indicates the indirect energy input required to produce $\bar{\mathbf{f}}_{pq}$. Similarly, the embodied capital input, labor input, value added, and CO_2 emissions can be calculated using capital coefficient vector $\mathbf{k}$, labor coefficient matrix $\mathbf{l}$, material coefficient matrix $\mathbf{m}$, value added coefficient matrix $\mathbf{v}$, and CO_2 emission coefficient $\mathbf{c}$, with dimensions of $PQ \times 1$, respectively.

Following the above, a dataset consisting of four inputs, one desirable output, and one undesirable output is constructed to measure supply chain performance via DEA. X_{pq}, Y_{pq}, and B_{pq} denote the inputs, desirable output, and undesirable output of sector q in country p, respectively. The input–output datasets for the manufacturer, supplier, and conventional models can be expressed as follows:

[Manufacturer model]

$$\begin{cases} X_{pq}^{capital} = \mathbf{k}^{\mathrm{T}}\mathbf{I}\bar{\mathbf{f}}_{pq} \\ X_{pq}^{labor} = \mathbf{l}^{\mathrm{T}}\mathbf{I}\bar{\mathbf{f}}_{pq} \\ X_{pq}^{energy} = \mathbf{e}^{\mathrm{T}}\mathbf{I}\bar{\mathbf{f}}_{pq} \\ X_{pq}^{material} = \mathbf{m}^{\mathrm{T}}\mathbf{I}\bar{\mathbf{f}}_{pq} \\ Y_{pq} = \mathbf{v}^{\mathrm{T}}\mathbf{I}\bar{\mathbf{f}}_{pq} \\ B_{pq} = \mathbf{c}^{\mathbf{T}}\mathbf{I}\bar{\mathbf{f}}_{pq} \end{cases} \tag{4}$$

[Supplier model]

$$\begin{cases} X_{pq}^{capital} = \mathbf{k}^{\mathrm{T}}\mathrm{AL}\bar{\mathbf{f}}_{pq} \\ X_{pq}^{labor} = \mathbf{l}^{\mathrm{T}}\mathrm{AL}\bar{\mathbf{f}}_{pq} \\ X_{pq}^{energy} = \mathbf{e}^{\mathrm{T}}\mathrm{AL}\bar{\mathbf{f}}_{pq} \\ X_{pq}^{material} = \mathbf{m}^{\mathrm{T}}\mathrm{AL}\bar{\mathbf{f}}_{pq} \\ Y_{pq} = \mathbf{v}^{\mathrm{T}}\mathrm{AL}\bar{\mathbf{f}}_{pq} \\ B_{pq} = \mathbf{c}^{\mathbf{T}}\mathrm{AL}\bar{\mathbf{f}}_{pq} \end{cases} \tag{5}$$

[Conventional model]

$$\begin{cases} X_{pq}^{capital} = \mathbf{k}^{\mathrm{T}}\mathbf{L}\bar{\mathbf{f}}_{pq} \\ X_{pq}^{labor} = \mathbf{l}^{\mathrm{T}}\mathbf{L}\bar{\mathbf{f}}_{pq} \\ X_{pq}^{energy} = \mathbf{e}^{\mathrm{T}}\mathbf{L}\bar{\mathbf{f}}_{pq} \\ X_{pq}^{material} = \mathbf{m}^{\mathrm{T}}\mathbf{L}\bar{\mathbf{f}}_{pq} \\ Y_{pq} = \mathbf{v}^{\mathbf{T}}\mathbf{L}\bar{\mathbf{f}}_{pq} \\ B_{pq} = \mathbf{c}^{\mathbf{T}}\mathbf{L}\bar{\mathbf{f}}_{pq} \end{cases} \tag{6}$$

World Input–Output Database is used for empirical analysis. It consists of 56 sectors in 43 countries and the rest of the world. Thus, P is 44 and Q is 56.

3.2. Measuring performance of supply chains using GML productivity index

The GML productivity index is applied to the datasets for the three models to measure performance of supply chains in each sector and country. Section 3.2.1 provides the underlying assumptions about the production possibility set (PPS) and the definition of the DDF. Then, section 3.2.2 explains the definition and decomposition of the GML productivity index.

3.2.1. PPS and DDF

This study separately models the PPS of each sector to account for sectoral heterogeneity in environmental performance [15]. Under a panel of $p = 1, \ldots, P$ countries, $q = 1, \ldots, Q$ sectors, and $t = 1, \ldots, T$ time periods, PPS $P_q(X_q)$ represents the production technology for sector q of the countries that produce M desirable outputs, $\mathbf{Y}_q \in R_+^M$, and N undesirable outputs, $\mathbf{B}_q \in R_+^N$, using O inputs, $\mathbf{X}_q \in R_+^O$. The PPS can be expressed as

$$P_q(X_q) = \{(\mathbf{Y}_q, \mathbf{B}_q) | \mathbf{X}_q \; can \; produce \; (\mathbf{Y}_q, \mathbf{B}_q)\} \tag{7}$$

Following Färe et al. [34,49], two assumptions are imposed on Eq. (7) to represent the actual characteristics of production technology.

(i) If $(\mathbf{Y}_q, \mathbf{B}_q) \in P_q(X_q)$ and $\mathbf{B}_q = 0$, then $\mathbf{Y}_q = 0$
(ii) $(\mathbf{Y}_q, \mathbf{B}_q) \in P_q(X_q)$ and $0 \le \theta \le 1$ imply $(\theta\mathbf{Y}_q, \theta\mathbf{B}_q) \in P_q(X_q)$.

Condition (i) formulates the null-jointness assumption, i.e., undesirable outputs are not eliminated unless the production of desirable outputs completely stops. Condition (ii) formulates the weak disposability assumption on undesirable outputs, i.e., it is costly to reduce undesirable outputs. Eq. (7), along with these assumptions, represents the environmental production technology of sector q.

This study utilizes the DDF approach to operationalize the abovementioned conceptual model [19,28,34]. The CRS PPS can be formulated as.

$$P_q(X_q) = \Big\{ (\mathbf{Y}_q, \mathbf{B}_q) : \sum_{p=1}^{P} \lambda_p \mathbf{X}_{pq} \le \mathbf{X}_q$$

$$\sum_{p=1}^{P} \lambda_p \mathbf{Y}_{pq} \ge \mathbf{Y}_q$$

$$\sum_{p=1}^{P} \lambda_p \mathbf{B}_{pq} = \mathbf{B}_q$$

$$\lambda_p \ge 0, p = 1, ..., P \Big\} \tag{8}$$

where λ is the intensity variable. Eq. (8) constructs a best practice frontier for sector q by incorporating the observations for P countries. The economic and environmental performances of the supply chains of sector q in a country can be measured using the distance between an observation and the best practice frontier.

This study adopts the DDF approach (Chung et al. [28]) for measuring efficiency. Let.

$\mathbf{g}_{pq} = (\mathbf{g}^B_{pq}, \mathbf{g}^Y_{pq})$ be a direction vector, where $\mathbf{g} \in R^M_+ \times R^N_+$. Direction vector $\mathbf{g}$ determines the direction of outputs, by which desirable outputs increase and undesirable outputs decrease. This study considers $\mathbf{g}_{pq} = (-B_{pq}, Y_{pq})$ following Chung et al. [28] and Oh [19]. Then, the DDF is defined as

$$D_{p'q}(\mathbf{X}_{p'q}, \mathbf{Y}_{p'q}, \mathbf{B}_{p'q}) = max \, \beta_{p'q}$$

$$s.t. \begin{cases} \sum_{p=1}^{P} \lambda_p \mathbf{X}_{pq} \le \mathbf{X}_{p'q} \\ \sum_{p=1}^{P} \lambda_p \mathbf{Y}_{pq} \ge (1 + \beta_{p'q}) \mathbf{Y}_{p'q} \\ \sum_{p=1}^{P} \lambda_p \mathbf{B}_{pq} = (1 - \beta_{p'q}) \mathbf{B}_{p'q} \\ \lambda_p \ge 0, p = 1, ..., P \end{cases} \tag{9}$$

where p' denotes the country under evaluation. This linear programming problem can be also expressed as $D_{p'q}(\mathbf{X}_{p'q}, \mathbf{Y}_{p'q}, \mathbf{B}_{p'q}) = max\{\beta_{p'q} | (1 + \beta_{p'q})\mathbf{Y}_{p'q}, (1 - \beta_{p'q})\mathbf{B}_{p'q} \in P_q(X_q)\}$. This function seeks the maximal increase in desirable outputs while decreasing undesirable outputs for sector q in country p'. The PPS and DDF are depicted in Fig. 3.

3.2.2. GML productivity index

The GML index is circular and overcomes the infeasibility problem of the Malmquist–Luenberger index (Oh [19]). Contemporaneous and global benchmark technologies are essential for defining and decomposing the GML index (Oh [19]). A contemporaneous benchmark technology constructs a reference production set in year t, and it is defined as $P^t_q(\mathbf{X}^t_q) = \{(\mathbf{Y}^t_q, \mathbf{B}^t_q) | \mathbf{X}^t_q \; can \; produce \; (\mathbf{Y}^t_q, \mathbf{B}^t_q)\}$, where $t = 1, ..., T$..

A global benchmark technology is defined as $P^G_q = P^1_q \cup P^2_q \cup \cdots \cup P^T_q$. This is an extended version of the global benchmark technology proposed by Paster and Lovell [50], which incorporates undesirable outputs. The global benchmark technology envelopes all contemporaneous benchmark technologies by establishing a single reference PPS from a panel dataset on the inputs and outputs of relevant DMUs (Oh [19]).

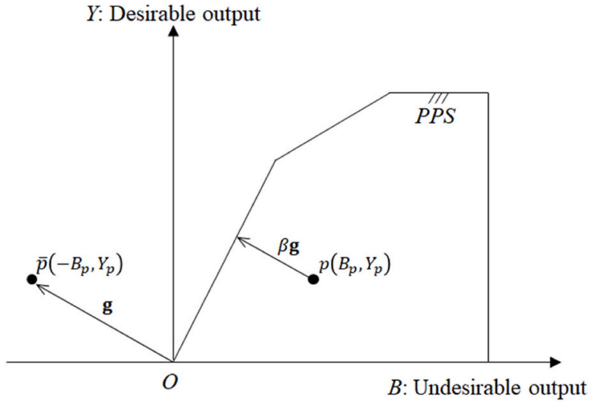

Fig. 3. PPS and DDF

The benchmark technologies are depicted in Fig. 4. The two interior solid lines are the contemporaneous technologies for years 1 and 2. Note that the remaining $T-2\ (t=3,\dots,T)$ contemporaneous benchmark technologies are not depicted in the figure for simplicity. The interior thick solid line is the global technology. Thus, the envelopment of all T contemporaneous benchmark technologies is equivalent to the global benchmark technology.

Following Oh [19], the GML index is defined as follows:

$$GML_{pq}^{t,t+1}\left(\mathbf{X}_{pq}^{t},\mathbf{Y}_{pq}^{t},\mathbf{B}_{pq}^{t},\mathbf{X}_{pq}^{t+1},\mathbf{Y}_{pq}^{t+1},\mathbf{B}_{pq}^{t+1}\right)=\frac{1+D_{pq}^{G}\left(\mathbf{X}_{pq}^{t},\mathbf{Y}_{pq}^{t},\mathbf{B}_{pq}^{t}\right)}{1+D_{pq}^{G}\left(\mathbf{X}_{pq}^{t+1},\mathbf{Y}_{pq}^{t+1},\mathbf{B}_{pq}^{t+1}\right)} \tag{10}$$

where the DDF, $D_{pq}^{G}(\mathbf{X}_{pq}^{t},\mathbf{Y}_{pq}^{t},\mathbf{B}_{pq}^{t})=max\{\beta_{pq}\big|(1+\beta_{pq})\mathbf{Y}_{pq}^{t},(1-\beta_{pq})\mathbf{B}_{pq}^{t}\in P_{q}^{G}(X_{q})\}$, is defined on the global benchmark technology set, $P_{q}^{G}(X_{q})$. If a production activity can produce more (less) desirable outputs and less (more) undesirable outputs, then $GML_{pq}^{t,t+1}>(<)1$, which indicates productivity gain (loss).

The GML index can be decomposed into two components of the productivity change (PCH) as follows:

$$\begin{aligned}
&GML_{pq}^{t,t+1}\left(\mathbf{X}_{pq}^{t},\mathbf{Y}_{pq}^{t},\mathbf{B}_{pq}^{t},\mathbf{X}_{pq}^{t+1},\mathbf{Y}_{pq}^{t+1},\mathbf{B}_{pq}^{t+1}\right)\\
&=\frac{1+D_{pq}^{G}\left(\mathbf{X}_{pq}^{t},\mathbf{Y}_{pq}^{t},\mathbf{B}_{pq}^{t}\right)}{1+D_{pq}^{G}\left(\mathbf{X}_{pq}^{t+1},\mathbf{Y}_{pq}^{t+1},\mathbf{B}_{pq}^{t+1}\right)}\\
&=\frac{1+D_{pq}^{t}\left(\mathbf{X}_{pq}^{t},\mathbf{Y}_{pq}^{t},\mathbf{B}_{pq}^{t}\right)}{1+D_{pq}^{t+1}\left(\mathbf{X}_{pq}^{t+1},\mathbf{Y}_{pq}^{t+1},\mathbf{B}_{pq}^{t+1}\right)}\times\left[\frac{1+D_{pq}^{G}\left(\mathbf{X}_{pq}^{t},\mathbf{Y}_{pq}^{t},\mathbf{B}_{pq}^{t}\right)\Big/1+D_{pq}^{t}\left(\mathbf{X}_{pq}^{t},\mathbf{Y}_{pq}^{t},\mathbf{B}_{pq}^{t}\right)}{1+D_{pq}^{G}\left(\mathbf{X}_{pq}^{t+1},\mathbf{Y}_{pq}^{t+1},\mathbf{B}_{pq}^{t+1}\right)\Big/1+D_{pq}^{t+1}\left(\mathbf{X}_{pq}^{t+1},\mathbf{Y}_{pq}^{t+1},\mathbf{B}_{pq}^{t+1}\right)}\right]\\
&=\frac{TE_{pq}^{t+1}}{TE_{pq}^{t}}\times\frac{BPG_{pq}^{t+1}}{BPG_{pq}^{t}}\\
&=ECH_{pq}^{t,t+1}\times TCH_{pq}^{t,t+1}
\end{aligned} \tag{11}$$

where TE_{pq}^{t} is technical efficiency, and BPG_{pq}^{t} is the best practice gap between a contemporaneous technology frontier in year t and a global technology frontier for sector q in country p. Hence, $ECH_{pq}^{t,t+1}$ is an efficiency change (ECH) term, which represents how closely a DMU moves towards a contemporaneous technology frontier in year t compared to year $t+1$. $TCH_{pq}^{t,t+1}$ is the change in the best practice gap between years t and $t+1$; it is a measure of the technical change (TCH) between the two time periods.

One can calculate and decompose the global Malmquist (GM) productivity index proposed by Paster and Lovell [50] by excluding undesirable outputs. Proposition 2 in the Appendix in Oh [19] explains the relation between the GML and GM indices when undesirable outputs are not included. The proposition indicates that the GML index without undesirable outputs is equivalent to the GM index, given $\mathbf{g}_{pq}=(\mathbf{g}_{pq}^{Y})=(Y_{pq})$. Hence, the GM and GML indices can be interpreted as the measures of the economic and environmental productivity change, respectively. Table 2 summarizes performance indices calculated in this study.

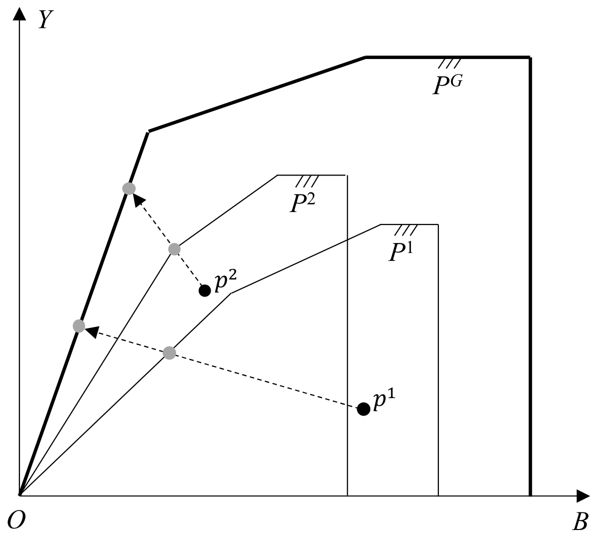

Fig. 4. Concept of benchmark technologies and GML index.

3.3. Data

This study applies the previously described methodology to evaluate the economic and environmental productivity change in supply chains in manufacturing sectors from 2000 to 2014. WIOD [17,18], which covers 56 sectors in 43 countries and rest of the world, is used to construct the input–output dataset for manufacturing sectors. Among the 56 sectors in WIOD, there are 18 manufacturing sectors, which are classified into three categories (i.e., labor, capital, and technology intensive sectors) following Wang et al. [15]. Table 1 presents the sector classification.[2]

The data for labor, capital, and material inputs are collected from the socio-economic accounts of WIOD [17], the data for the energy input and CO_2 emissions are collected from the environmental accounts of WIOD [18], and the data for the desirable output are obtained from the World Input–Output Table [17]. This study uses the labor compensation, nominal capital stock, and intermediate inputs in a monetary unit as labor, capital, and material inputs, respectively. The emission relevant energy use in a physical unit is considered as the energy input. All the data in the monetary unit are deflated to the constant 2010 USD price using the price index and exchange rates published by WIOD. The descriptive statistics of the dataset are provided in Table B1 (Appendix B).

4. Results and discussion

The GML and GM indices are decomposed into the efficiency change (ECH) and technical change (TCH) indices. The GML index measures the environmental productivity change (PCH), which considers undesirable outputs (CO_2 emissions), while the GM index measures the economic PCH, which does not consider undesirable outputs. The GML decomposition approach (hereinafter referred to as the GML measure) and GM decomposition approach (hereinafter referred to as the GM measure) are applied to the 18 manufacturing sectors listed in Table 1 for the manufacturer, supplier, and conventional models.

In the supplier model, the inputs are used by upstream production activities and emissions are generated from upstream production activities. There are considerable upstream production activities for final goods production in a sector in different countries. In other words, there are numerous suppliers for final goods production. This study aggregates these upstream production activities (or suppliers) and considers them as a single DMU based on the input–output model (see Eqs. (4)–(6) in section 3.2). Therefore, the aggregated DMU can be considered as a composite supplier for the final demand in a sector in different countries. The conventional model considers the sum of the direct and indirect inputs and the total CO_2 emissions in the entire supply chain of final goods production in a sector in different countries. Hence, the manufacturer, supplier, and conventional models measure the PCH in the production activity (manufacturer model), supplier network (a composite supplier for the final production demand, i.e., supplier model), and overall supply chain of a sector in different countries, respectively.

4.1. Comparison of patterns of productivity growth between three models

Fig. 5(a)–(i) show the Gaussian kernel density plots for the cumulative PCH, ECH, and TCH indices for the three models from 2000 to 2014. The solid and dotted lines indicate the plots for the GML and GM measures, respectively. The red, green, and blue lines

[2] Although the data of 43 countries are documented in WIOD, certain countries are excluded in the DEA. Thus, the number of countries analyzed in this study is different owing to data unavailability. The last column of Table 1 shows the number of DMUs in each sector.

Table 2
Indices calculated in this study.

Model	Model	Description
Manufacturer model	GML index	This measures environmental productivity change of production activity by a specific sector of a country. When the index is larger (smaller) than 1, environmental productivity of production activity of the sector improves (declines).
	GM index	This measures economic productivity change of production activity by a specific sector of a country. When the index is larger (smaller) than 1, economic productivity of production activity of the sector improves (declines).
Supplier model	GML index	This measures environmental productivity change of production activity of upstream suppliers for a specific sector of a country. When the index is larger (smaller) than 1, environmental productivity of production activity of upstream suppliers for the sector improves (declines).
	GM index	This measures economic productivity change of production activity of upstream suppliers for a specific sector of a country. When the index is larger (smaller) than 1, economic productivity of production activity of upstream suppliers for the sector improves (declines).
Conventional model	GML index	This measures environmental productivity change of production activity of entire supply chain associated with a specific sector of a country. When the index is larger (smaller) than 1, environmental productivity of production activity of entire supply chain associated with the sector improves (declines).
	GM index	This measures economic productivity change of production activity of entire supply chain associated with a specific sector of a country. When the index is larger (smaller) than 1, economic productivity of production activity of entire supply chain associated with the sector improves (declines).

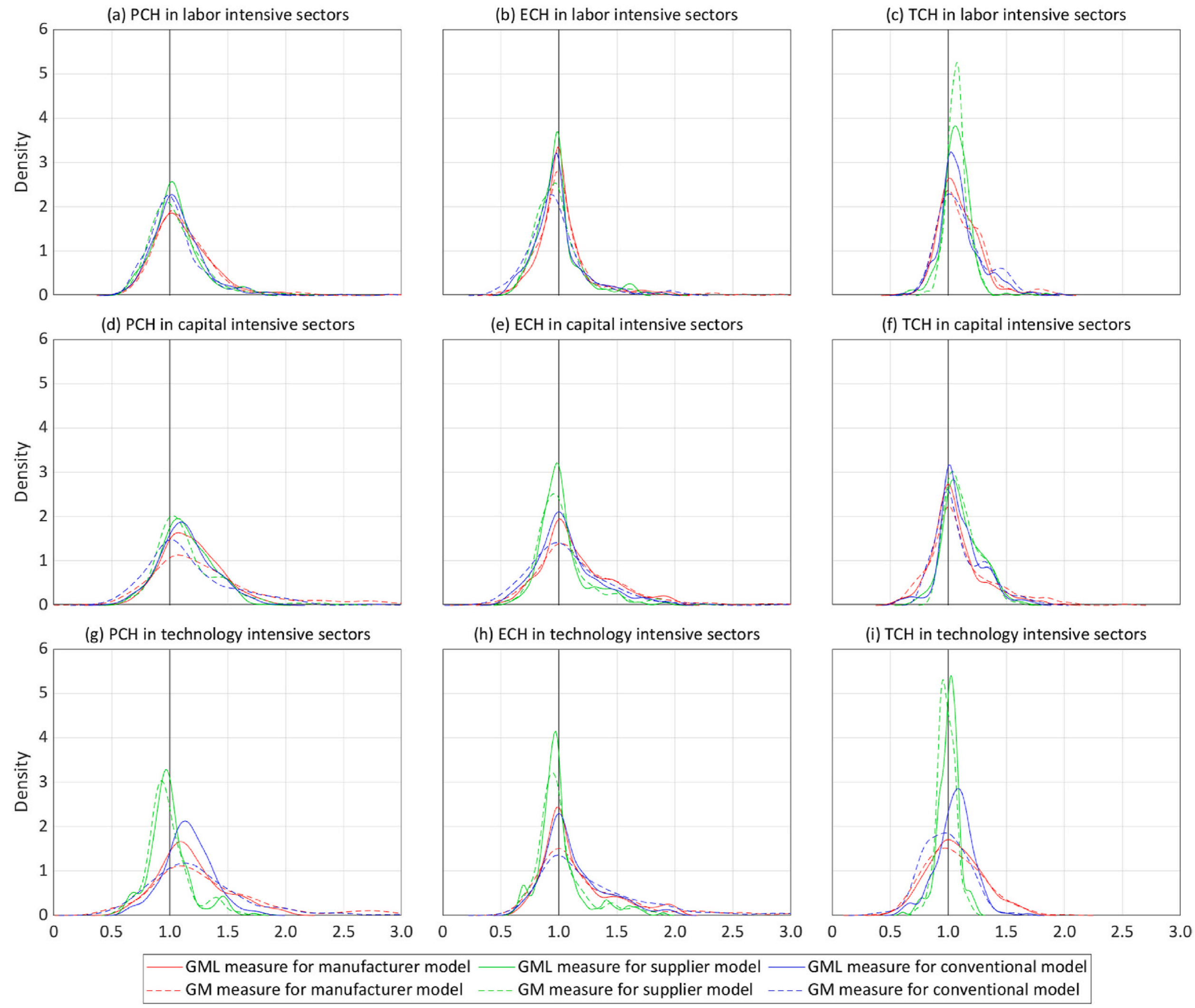

Fig. 5. Gaussian kernel density plots for GML and GM indices in three aggregated sectors.

Table 3
Cumulative changes in GML and GM indices for three models from 2000 to 2014.

	Manufacturer model						Supplier model						Conventional model					
	GML measure			GM measure			GML measure			GM measure			GML measure			GM measure		
	PCH	ECH	TCH	PCH	ECH	TCH	PCH	ECH	TCH	PCH	ECH	TCH	PCH	ECH	TCH	PCH	ECH	TCH
L.1	1.11	1.04	1.07	1.17	1.09	1.08	1.10	0.98	1.12	1.15	1.01	1.14	1.08	1.00	1.08	1.09	1.00	1.09
L.2	1.15	1.02	1.13	1.20	1.01	1.19	1.01	0.99	1.03	1.04	0.97	1.08	1.08	0.95	1.13	1.05	0.86	1.21
L.3	1.07	1.05	1.02	1.09	1.06	1.02	1.13	1.03	1.09	1.19	1.08	1.10	1.03	1.02	1.01	1.03	1.04	1.00
L.4	1.04	1.05	0.99	1.05	1.10	0.95	1.02	0.99	1.02	1.03	1.00	1.03	1.02	1.04	0.98	0.97	1.05	0.93
L.5	1.00	1.01	0.99	0.99	0.99	0.99	0.98	0.92	1.06	0.91	0.90	1.01	0.95	0.98	0.97	0.91	0.98	0.93
L.6	1.12	0.90	1.24	1.16	0.86	1.35	0.96	0.91	1.05	0.92	0.88	1.05	1.09	0.84	1.30	1.09	0.77	1.41
Sectoral mean	1.08	1.01	1.08	1.11	1.01	1.10	1.03	0.97	1.06	1.04	0.97	1.07	1.04	0.97	1.08	1.03	0.94	1.09
C.1	1.27	1.30	0.98	1.90	1.64	1.16	1.26	1.08	1.17	1.35	1.16	1.16	1.31	1.04	1.26	1.49	1.09	1.36
C.2	1.14	0.97	1.17	1.20	0.91	1.32	1.20	0.96	1.25	1.20	0.96	1.24	0.99	0.81	1.23	0.87	0.71	1.23
C.3	1.10	1.19	0.93	1.06	1.20	0.89	1.14	0.98	1.17	1.13	0.91	1.23	1.19	1.15	1.03	1.00	1.10	0.91
C.4	1.09	1.08	1.01	1.09	1.10	0.99	1.05	1.00	1.05	1.06	1.00	1.06	1.07	1.09	0.99	1.09	1.11	0.98
C.5	1.16	1.15	1.01	1.21	1.25	0.97	1.05	0.99	1.06	1.06	0.98	1.08	1.10	1.10	1.00	1.11	1.14	0.97
C.6	1.27	1.03	1.24	1.41	1.13	1.25	1.11	1.02	1.09	1.08	1.06	1.02	1.28	1.12	1.14	1.36	1.14	1.19
C.7	1.12	1.05	1.06	1.13	1.06	1.06	1.02	1.04	0.98	1.00	1.02	0.99	1.01	1.01	1.00	1.02	1.00	1.02
Sectoral mean	1.16	1.11	1.04	1.25	1.16	1.07	1.12	1.01	1.11	1.12	1.01	1.11	1.12	1.03	1.08	1.10	1.02	1.08
T.1	1.06	1.23	0.87	1.18	1.47	0.81	0.93	0.97	0.96	0.92	0.99	0.93	1.08	1.08	0.99	1.27	1.50	0.85
T.2	1.16	1.11	1.04	1.25	1.19	1.05	0.97	0.99	0.98	0.93	0.98	0.95	1.13	1.10	1.03	1.26	1.30	0.97
T.3	1.16	1.10	1.05	1.24	1.17	1.06	0.99	0.99	1.00	0.96	0.97	0.99	1.10	1.09	1.01	0.97	1.11	0.87
T.4	1.08	0.99	1.09	1.10	0.97	1.14	1.04	1.02	1.03	1.04	1.03	1.02	1.12	1.05	1.08	1.18	1.08	1.09
T.5	1.30	1.11	1.17	1.40	1.25	1.12	0.98	0.97	1.01	0.98	0.97	1.01	1.27	1.13	1.13	1.21	1.20	1.01
Sectoral mean	1.15	1.11	1.04	1.23	1.20	1.02	0.98	0.99	1.00	0.97	0.99	0.98	1.14	1.09	1.04	1.17	1.23	0.95
Grand mean	1.13	1.07	1.05	1.20	1.12	1.07	1.05	0.99	1.06	1.05	0.99	1.06	1.10	1.03	1.07	1.09	1.05	1.05

indicate the plots for the manufacturer, supplier, and conventional models, respectively. Fig. 5(a) shows that the peaks of the six density plots are almost the same; however, their distribution are not the same. As shown in Fig. 5(i), the peak and the distribution differ by six density plots. Different patterns are observed for the manufacturer, supplier, and conventional models; thus, it is worthwhile to compare the PCH index between the three models.

This study employs two nonparametric tests that are commonly used in efficiency and productivity analysis to verify whether the patterns of productivity growth are the same between the three models. First, the Wilcoxon signed-rank test is used to test the null hypothesis that the models have the same ranks for cumulative PCH indices. Second, the two-sample Kolmogorov–Smirnov test is applied to test the null hypothesis that cumulative PCH indices of the models results from the same distribution. These tests are used because similar distributions of the PCH index may yield different ranks between the models, or *vice versa*. If distributions or ranks are different between the models, then the patterns of productivity growth are also different. If the patterns of productivity growth are different between the manufacturer, supplier and conventional models, the manufacturer and supplier models could provide implication that could not be revealed by the conventional model.

Table D1(Appendix D) summarizes the results of the Wilcoxon signed-rank test and two-sample Kolmogorov–Smirnov test. Table D1(a) shows that the ranks of the manufacturer and supplier models are different at a significance level of 5% in all sectors. In addition, Table D1(b) shows that the null hypothesis (manufacturer and supplier models have the same distribution) is rejected at a significance level of 5% in all sectors. Therefore, the patterns of environmental and economic productivity growth are significantly different between the production activity and supplier network in all sectors.

The comparison of the manufacturer and conventional models shows that the ranks and distribution are different at a significance level of 5% for the GM measure in labor- and capital-intensive sectors. Although the distribution is not significantly different, the ranks are different at a significance level of 5% for the GML measure in labor- and capital-intensive sectors and the GM measure in technology intensive sectors. Thus, the patterns of productivity growth are different. In contrast, Table D1 (a-iii and b-iii) shows that the patterns of productivity growth are the same at a significance level of 5% for the GML measure in technology intensive sectors. The comparison of the supplier and conventional models shows that the ranks and distribution of the cumulative PCH under the GML and GM measures are significantly different in technology intensive sectors. Conversely, they are the same in labor- and capital-intensive sectors at a significant level of 5%. Therefore, the patterns of environmental and economic productivity growth are similar between the supplier and conventional models, except in technology intensive sectors.

4.2. Productivity change in labor, capital, and technology intensive manufacturing sectors

Table 3 summarizes the geometric mean of the cumulative PCH, ECH, and TCH indices from 2000 to 2014 for the manufacturer, supplier, and conventional models.[3] Note that the PCH index is a product of the ECH and TCH indices (see Eq. (11) in section 3.2).

The grand mean of the PCH index for the GML measure in the manufacturer model is 1.13, indicating that the environmental productivity of the production activity of 18 manufacturing sectors improved by 13 percent during 2000–2014 on average. The productivity of the transport equipment sector (T.5) experienced the highest growth of 30.1% during the study period. For the GML measure in the manufacturer model, the grand mean of the ECH (1.07) is larger than that of the TCH (1.05). This implies that the ECH and TCH contribute to the improvement of the environmental productivity of the production activity. In addition, the contribution of the ECH (catching up to the frontier) to the productivity growth is higher than that of the TCH (shifting of the frontier). The grand mean of the PCH for the GM measure (1.20) is larger than that for the GML measure (1.13). This indicates that the environmental productivity growth in the production activity of 18 sectors is not as high as the economic productivity growth due to environmental regulation.

The grand mean of the PCH for the GML measure in the supplier model (1.05) is smaller than that in the manufacturer model. Therefore, the environmental productivity growth in the supplier network is lower than that in the production activity of 18 manufacturing sectors during the study period. The grand mean of the ECH for the GML measure in the supplier model is 0.99. Thus, the ECH contributes to the productivity decline in the supplier network of 18 manufacturing sectors. In contrast, the grand mean of the TCH for the GML measure in the supplier model is 1.06, which indicates that the TCH contributes to productivity growth. This study reveals that environmental productivity tends to decline in the supplier network of technology intensive sectors (T.1–T.5) because the PCH for the GML measure in the supplier model is lower than unity, except for the motor vehicle sector (T.4). This could be interpreted as follows: the supplier network of technology intensive sectors becomes more inefficient and CO_2 emission intensive during the study period. The productivity decline in technology intensive sectors is not observed in the conventional model because the model does not distinguish between the performance of the production activity and supplier network. The proposed framework can distinguish between the performance of the production activity and supplier network. Appendix C provides results for cumulative change in ECH and TCH indices for labor, capital, and technology intensive sectors for the manufacturer, supplier, conventional models from 2000 to 2014.

Most of the existing studies (e.g., Refs. [5,11,33]) focus only on the direct production activity (i.e., manufacturer model) in their efficiency analysis. Recently, Wang [15] and Henrique [16] have focused on the performance of the entire supply chain by combining direct production activity and upstream production activity (conventional model). The model proposed in this study evaluates the performance of direct production activity and upstream production activity separately by decomposing the conventional model into

[3] Note that the GML and GM indices represent the productivity growth rate, and they are calculated as the product of ECH and TCH. Therefore, this study uses geometric mean rather than arithmetic mean.

manufacturer model and supplier model.

Taking the GML measure of sector L.6 as an example, the PCH index in the manufacturer model is 1.12, while the PCH index in the conventional model is 1.09. On the other hand, the PCH index in the supplier model is 0.96, indicating that the environmental performance of the upstream production activity has declined. This suggests that the increase in the environmental performance of the entire supply chain in sector L.6 is mainly due to environmental productivity improvements in direct production activities (production technology improvements).

Compared with the conventional model used in Wang [15] and Henrique [16], the proposed model can separately analyze the performance of supply chains. With the acceleration of international trade in recent years [9,42,52], there has been increasing interest in emissions transfers, i.e. the relocation of polluting industries to other countries. It is therefore important to assess the performance of manufacturing sectors in different countries separately for the production and supply phases.

4.3. Changes in economic productivity and environmental productivity

In this section, the GM and GML indices are compared to investigate the patterns of economic and environmental productivity growth at disaggregated sector and country levels. Fig. 6 shows the cumulative change in the GM and GML indices from 2000 to 2014 in labor, capital, and technology intensive sectors for the manufacturer, supplier, and conventional models. Each marker represents a country, and the shape and color of the marker indicate a disaggregated manufacturing sector (see Table 1 for the sector classification). The geometric means of the GM index ($\overline{\text{GM}}$) and GML index ($\overline{\text{GML}}$) are provided in each figure. For example, Fig. 6(a) shows that the average GM and GML indices for the manufacturer model are 1.113 and 1.084, respectively, in labor intensive sectors (L.1–L.6). Fig. 6 (a)–(i) illustrate that there is a positive correlation between economic and environmental productivity growth.

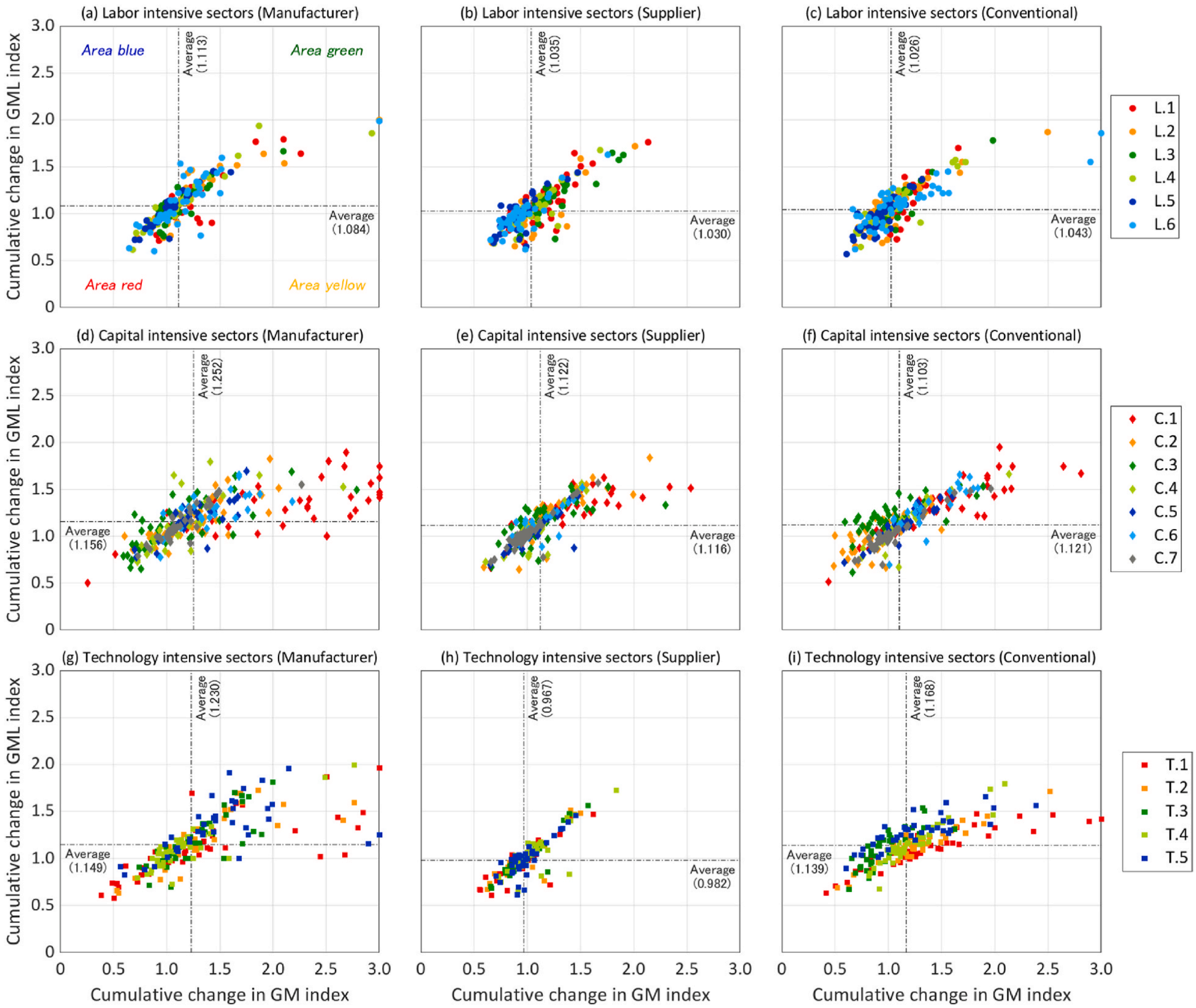

Fig. 6. Cumulative changes in GML and GM indices from 2000 to 2014.

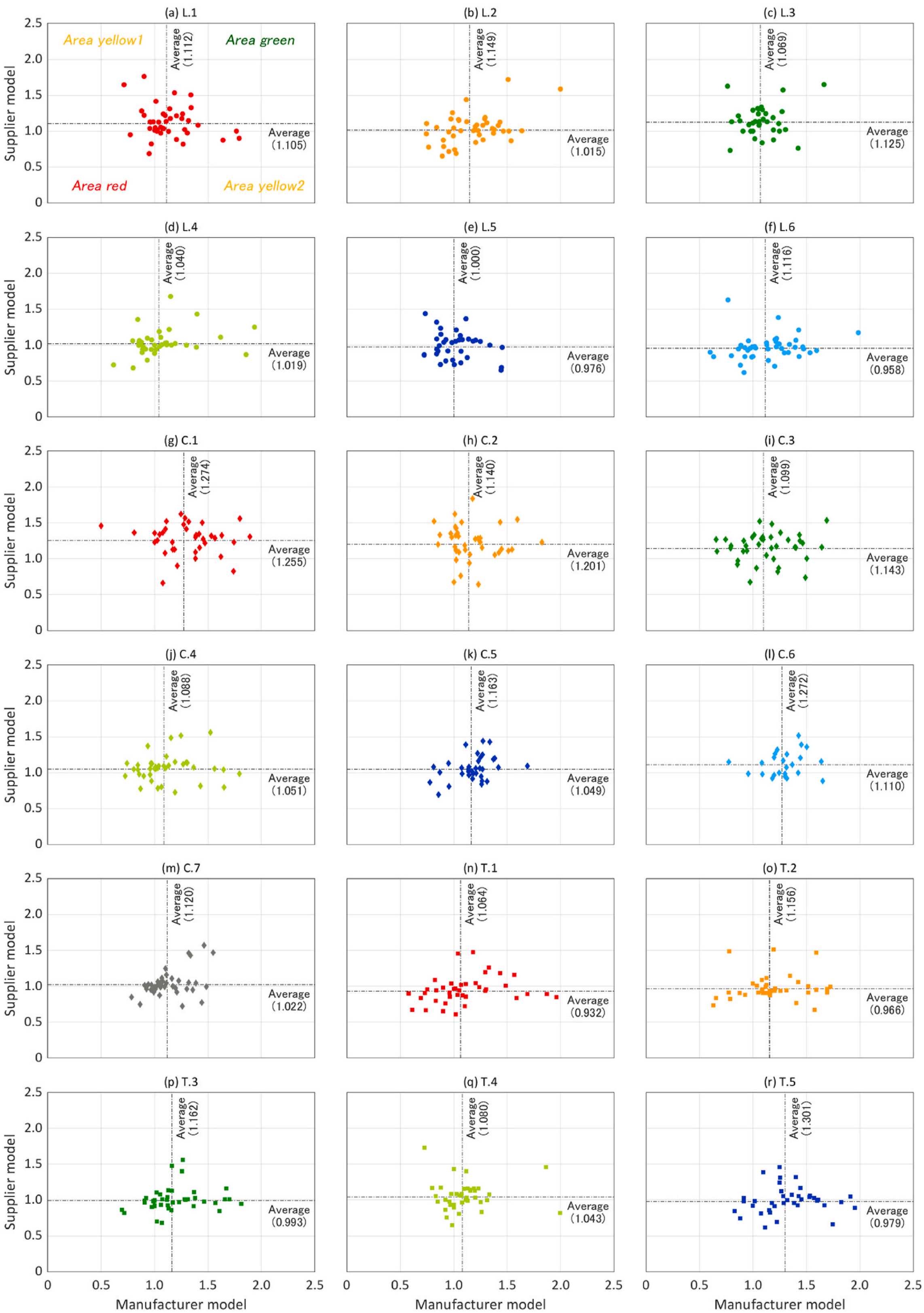

Fig. 7. Cumulative changes in GML index for manufacturer and supplier models.

This study defines green, blue, yellow, and red areas based on Fig. 6(a)–(i). The GM and GML indices for a country located in the green area (hereinafter referred to as a green country) are equal to or larger than $\overline{\mathrm{GM}}$ and $\overline{\mathrm{GML}}$. Thus, the economic and environmental productivity growth in a green country is larger than the average during the study period. On the contrary, the GM and GML indices for a country located in the red area (hereinafter referred to as a red country) are smaller than unity. This indicates that the economic and environmental productivity of a red country decreased from 2000 to 2014. In a country in the blue area, the GM index is smaller than unity and the GML index is larger than $\overline{\mathrm{GML}}$. In a country in the yellow area, the GM index is larger than $\overline{\mathrm{GM}}$ and the GML index is smaller than unity. Therefore, the economic productivity of a country in the blue area declines, but the environmental productivity growth is larger than the average. The opposite trend is observed for a country in the yellow area. Note that the overlapping area between the blue and yellow areas ($1 \leq \mathrm{GM} < \overline{\mathrm{GM}}$ *and* $1 \leq \mathrm{GML} < \overline{\mathrm{GML}}$) is defined as the blue area. Appendix E presents the list of green and red countries.

4.4. Relation between environmental productivity of manufacturer and supplier models

This section focuses on the GML index for the manufacturer and supplier models. It is important for policy makers in each country to understand which sector succeeds (fails) to improve environmental productivity. Moreover, understanding the environmental performance of the production activity and supplier network is useful for decision makers to discuss industry-specific management policies for reviewing the production activity and supplier network. If environmental productivity in a sector of a country declines in the manufacturer model, the country needs to implement technology-oriented policy to the sector (e.g., promoting low-carbon technology through subsidy, taxing, and emission trading scheme). If environmental productivity in a sector of a country declines in the supplier model, the country needs to implement policy regarding supply chain management (e.g., promoting green procurement).

Fig. 7(a)–(r) show the cumulative changes in the GML index for the manufacturer and supplier models from 2000 to 2014 in 18 manufacturing sectors. The geometric means of the GML index for the manufacturer and supplier models in each sector are also presented. For example, Fig. 7(a) shows that the geometric means of the GML index for manufacturer and supplier models are 1.112 and 1.105, respectively. This indicates that the environmental productivity of the production activity and supplier network of sector L.1 improved during the study period. The same trend can be observed in sectors L.2, L.3, L.4, C.1–C.7, and T.4. All capital-intensive sectors have achieved environmental productivity growth in the production activity and supplier network. In sector L.6, the average environmental productivity improves for the manufacturer model but declines for the supplier model. The same trend is observed for technology intensive sectors (except sector T.4). Although the environmental productivity of these sectors has improved, the performance of upstream suppliers of these sectors has become environmentally inefficient.

As shown in Fig. 7, there is a weak correlation between the environmental PCH for the manufacturer and supplier models. Thus, the management and performance of the production activity and supplier network differ according to countries. The countries are divided into green, yellow1, yellow2, and red areas based on the environmental PCH for the manufacturer and supplier models. In a country located in the green area, the environmental productivity of the manufacturer and supplier models is more than the global average. On the contrary, the environmental productivity of the manufacturer and supplier models declines in a country located in the red area. The yellow1 and yellow2 areas are defined in the same manner as the blue and yellow areas in section 4.3, respectively. In a country in the yellow1 area, the environmental productivity of the production activity declines and that of the supplier network is more than the global average. The opposite trend is observed for a country in the yellow2 area.

Appendix F provides the list of the green and red countries shown in Fig. 7. Table F1 shows the green and red countries in 18 sectors. The number of countries in labor, capital, and technology intensive sectors is 237, 254, and 197, respectively. Among these, there are 28%, 30%, and 26% green countries and 19%, 8%, and 20% red countries in labor, capital, and technology intensive sectors, respectively. There are more red countries in labor and technology intensive sectors compared to capital intensive sectors. Therefore, it is particularly important for these sectors to enhance their environmental efficiency by improving production technology and supply chain management according to the best practice frontier.

4.5. Theoretical contributions

As globalization progresses and supply chain structures become more complex, many studies have used the EEMRIO approach to estimate CO_2 emissions based on consumption-based and production-based accounting. By combining the EEMRIO approach with the DEA approach, this study developed a model to assess the environmental performance of the manufacturing supply chain separately for the manufacturing and supplying phases. In general, direct production activities often involve moving production to countries with cheaper labor or changing the source of materials to reduce costs. If a particular country changes its choice of suppliers, this may also lead to changes in the production activities of the upstream supply chain, changing the environmental performance of the upstream production activity.

For example, in sector T.2, the environmental productivity of the manufacturer model has improved on average by 15.6% during the study periods, while the environmental productivity of the supplier model has declined on average by 3.4%. In other words, changes in production technology and supply chain management in sector T.2 have allowed for generating more value-added with less environmental impact in the direct production activity. On the other hand, changes in production technology and supply chain management in sector T.2 can be attributed to the decline in environmental productivity in the upstream production activity.

As for sector C.1, environmental productivity in both manufacturer and supplier models has improved by 27.4% and 25.5% on average, respectively. This indicates that changes in production technology and supply chain management in sector C.1 have contributed to improving the environmental productivity of direct and upstream production activity.

Using the proposed model, it is possible to further investigate the impact of supplier selection on the performance of entire supply chains. Although Fig. 7 does not show a strong correlation between environmental productivity in the manufacturer model and the supplier model, the use of panel data statistical analysis would provide theoretical insights into how supplier selection affects the performance of both direct production activities and upstream production activities, thus contributing to the understanding of supply chain management.

5. Conclusion

This study developed a novel framework that combined DEA and MRIO database to investigate the economic and environmental productivity change in the global supply chains associated with manufacturing sectors. Empirical analysis was performed for 18 manufacturing sectors in 43 countries from 2000 to 2014. The ECH and TCH indices were examined at the aggregated sector level. Compared with the previous cross-country DEA studies, the proposed framework enabled us to separately analyze the productivity change in the production activity (manufacturer model) and supplier network (supplier model) of a sector in different countries.

Patterns of the productivity change for the manufacturer, supplier, and conventional models were compared using two nonparametric tests. From the tests, different patterns of economic and environmental productivity growth were observed between the production activity and supplier network in all manufacturing sectors. Except for the patterns of environmental productivity growth in technology intensive sectors, the trends of economic and environmental productivity growth were different for the manufacturer and conventional models. In addition, the trends of economic and environmental productivity growth for the supplier and conventional models in technology intensive sectors were different. These results suggest that the performance of an entire supply chain should be separately analyzed from the performance of the production activity and supplier network.

The proposed framework can be used to identify a sector of countries succeed (fail) to improve economic and environmental performance. In the red countries listed in Table E1, both economic and environmental productivity declined during the study period. The red countries in the manufacturer model must improve their production technology and those in the supplier model must reconsider their supply chain management. In addition, both environmental productivity for the manufacturer and supplier models declined in the red countries listed in Table F1. There were more red countries in labor and technology intensive sectors compared to capital intensive sectors. Countries need to focus on sectors identified as red and implement industry-specific policies toward CO_2 mitigation.

To mitigate CO_2 emissions in the entire supply chain, each country needs to review its production and supply chain management. Regarding production management, it is important to improve production technology with awareness of life cycle assessment and Scope 1, 2, and 3 emissions (GHG Protocol [51]; Takayabu et al. [5]). For example, electrification in a sector reduces direct emission (Scope 1 emissions) from the sector, while it increases indirect emissions associated with electricity consumption (Scope 2 emissions) from the sector. Regarding supply chain management, supplier selection and restructuring supply chains contribute to significant CO_2 reduction (Maeno et al. [52]). Estimating Scope 3 emissions allows industrial sectors to identify hotspots of their supply chains and provides insights for restructuring their supply chains. Implementation of green procurement policies could provide an incentive to companies to review their supplier selection (Vejaratnam et al. [53]). From the DEA results, we can identify which country succeed to improve environmental productivity of production activity and supplier network. Policy makers could obtain managerial insights into production and supply chain management from those green countries.

Although the proposed framework is useful for separately analyzing supply chain performance as the manufacturing phase and supplying phase, it has the limitation that the supplier model considers all suppliers (e.g., energy, material, and service suppliers) for a sector as a composite DMU. With growing trade and specialization, global supply chains have become longer and more complex, and it becomes more difficult to identify key supply chain paths from the production network. A multistage network DEA model could also be utilized to extend the supplier model [36,39]. In future, it would be meaningful to further investigate the relationship between the participation in global supply chains and the environmental productivity change. The results would be useful for discussing policy measures that could better promote environmental performance during globalization.

Data availability

The input data used in the study can be found in the Supplementary materials.

CRediT authorship contribution statement

Hirotaka Takayabu: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

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

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Appendix A. Supplementary data

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