Estimates of Embodied Global Energy and Air-Emission Intensities of Japanese Products for Building a Japanese Input–Output Life Cycle Assessment Database with a Global System Boundary

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Ⓢ *Supporting Information*

ABSTRACT: To build a life cycle assessment (LCA) database of Japanese products embracing their global supply chains in a manner requiring lower time and labor burdens, this study estimates the intensity of embodied global environmental burden for commodities produced in Japan. The intensity of embodied global environmental burden is a measure of the environmental burden generated globally by unit production of the commodity and can be used as life cycle inventory data in LCA. The calculation employs an input–output LCA method with a global link input–output model that defines a global system boundary grounded in a simplified multiregional input–output framework. As results, the intensities of embodied global environmental burden for 406 Japanese commodities are determined in terms of energy consumption, greenhouse-gas emissions (carbon dioxide, methane, nitrous oxide, perfluorocarbons, hydrofluorocarbons, sulfur hexafluoride, and their summation), and air-pollutant emissions (nitrogen oxide and sulfur oxide). The uncertainties in the intensities of embodied global environmental burden attributable to the simplified structure of the global link input–output model are quantified using Monte Carlo simulation. In addition, by analyzing the structure of the embodied global greenhouse-gas intensities we characterize Japanese commodities in the context of LCA embracing global supply chains.
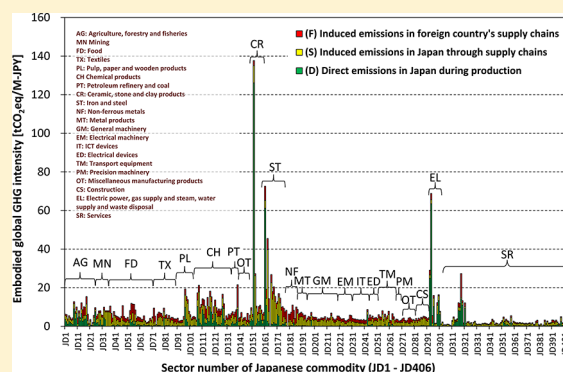
1. INTRODUCTION

Life cycle assessment (LCA) practitioners can adopt three types of approach to compile a Life Cycle Inventory (LCI): a process approach, an input–output approach, or a combination of the two: a hybrid approach.[1,2] Each has its strengths and weaknesses in terms of data resolution and the completeness and clarity of the system boundaries. In practice, and to a varying extent, all three approaches make use of existing LCA databases to reduce the time and resources required to collect raw data from the field. Today, there are a wide range of extensive LCA databases available suitable for use either in process-based LCA[3] or input–output LCA[4−11] (also a recent discussion on international guidance on LCA data[12]).

Process-based LCA allows sequential inclusion of data on the greenhouse gas (GHG) emissions associated with the imports used in a supply chain in order of data availability. Some of the existing process-based LCA databases[13,14] can therefore be used to estimate the emissions due to global supply chains. However, process-based LCA has difficulty guaranteeing the completeness of global supply chain descriptions and may sometimes even fail to detect key emission sources meriting preferential control in the supply chain

Input–output LCA, on the other hand, theoretically guarantees the completeness of global supply chain descriptions by adopting the framework of a multiregional input–output (MRIO) model.[15−17] Input–output LCA with MRIO is therefore more suitable for identifying global supply chains with high GHG emissions and for prioritizing processes for which inventory data

should be elaborated. Several case studies employing such a hybrid methodology have recently been published.[18,19]

In reality, however, as can be surmised from recent empirical analyses using MRIO,[20−28] it is no simple matter to build an input−output LCA database with MRIO in which the system boundary is globally extended to encompass the detailed sectoral classifications readily available for LCA. As explained in our previous article,[29] two approaches are available for overcoming the dilemma of high sectoral resolution and the attendant large labor burden. One is to develop a methodology and software that automates as far as possible the process of preparing the economic and environmental data;[30,31] the other is to employ a simplified MRIO modeling framework tailored to the specific purpose of the analysis. Adopting the latter approach, a global link input−output (GLIO) model was developed.[29,32]

In this article, the aim of which is to build an input−output LCA database of Japanese products based on a global system boundary in a manner involving lower time and labor burdens, we calculate the intensities of embodied global environmental burden (hereafter, global intensities) of commodities produced in Japan using the GLIO model. The environmental burdens considered here newly include energy consumption and air-pollutant emissions in addition to GHG emissions complied in the previous article.[29] Furthermore, given that the GLIO model is built around a simplified MRIO structure, uncertainties in the global intensities deriving from this simplification are quantified using Monte Carlo simulation. Finally, we analyze the characteristics of the derived global intensities focusing particularly on GHG emissions from the perspective of use in LCA embracing global supply chains.

2. METHODS AND DATA

2.1. Derivation of an Intensity of Embodied Global Environmental Burden.
This study applied the GLIO model specifying the global supply chains of Japanese commodities (goods and services) to calculate the intensity of embodied global environmental burden (energy consumption, GHG, and air-pollutant emissions) of these commodities. For instance, the embodied global GHG emission intensity (tCO_2eq/one million Yen: M-JPY) is a measure of the global GHG emissions (in Japan and abroad) induced by unit production activity in Japan equivalent to one million yen of the commodity in question. Because the global intensity of each commodity is derived using input−output analysis based on the same system boundary, this approach permits intercommodity comparison of these global intensities. Calculating these global intensities is conceptually identical to conducting an LCI of the commodity. Here, the life cycle stages considered are from cradle to gate, that is from resource mining through to manufacturing, and the functional unit of LCI is defined as unit production activity of the commodity in question.

As the structure of the GLIO model has already been described in a previous article,[29,32] and given space constraints here, the accounting framework and model formulation are set out in detail in the Supporting Information. Here, suffice it to say that from eq 1 below we can ultimately obtain the vectors $\mathbf{e}^{JD(i_1=\alpha)} = (e_{j_1}^{JD(i_1=\alpha)})$ and $\mathbf{e}^{G(i_1=\alpha)} = (e_p^{G(i_1=\alpha)})$, in which elements $e_{j_1}^{JD(i_1=\alpha)}$ and $e_p^{G(i_1=\alpha)}$ represent the environmental burden of sector $j_1 = 1...n^{JD}$ in Japan and in foreign country $p = 1...n^G$ induced by Japanese commodity $i_1 = \alpha$. Eq 2, summing these elements, then yields the intensity of embodied global environmental burden of the

commodity $e^{(i_1=\alpha)}$ indicating the global environmental burden induced by unit production (M-JPY) of commodity α in Japan.

$$
\begin{pmatrix} \mathbf{e}^{JD(i_1=\alpha)} \\ 0 \\ \mathbf{e}^{G(i_1=\alpha)} \end{pmatrix} = \text{diag} \begin{pmatrix} \mathbf{d}^{JD} \\ 0 \\ \mathbf{i}^G \end{pmatrix} \left\{ \mathbf{I} - \begin{pmatrix} \mathbf{A}_{11} & 0 & \tilde{\mathbf{A}}_{13} \\ 0 & 0 & 0 \\ \sum_{k=1}^{l} \tilde{\mathbf{A}}_{31}^{(k)} & \sum_{k=1}^{l} \tilde{\mathbf{A}}_{32}^{(k)} & \sum_{k=1}^{l} \tilde{\mathbf{A}}_{33}^{(k)} \end{pmatrix} \right\}^{-1} \begin{pmatrix} \mathbf{i}^{JD(i_1=\alpha)} \\ 0 \\ 0 \end{pmatrix}
$$

(1)

$$
e^{(i_1=\alpha)} = \sum_{j_1=1}^{n^{JD}} e_{j_1}^{JD(i_1=\alpha)} + \sum_{p=1}^{n^G} e_P^{G(i_1=\alpha)}
$$

(2)

where $\mathbf{A}_{11}[\, n^{JD} \times n^{JD}]$ is an input coefficient matrix defining the supply chains pertaining to Japanese domestic commodities i_1 and j_1 and $\tilde{\mathbf{A}}_{13}[n^{JD} \times n^G]$ is an input coefficient matrix defining the export structure of Japanese domestic commodity i_1 to overseas country q. Matrix $\tilde{\mathbf{A}}_{31}^{(k)}[\, n^G \times n^{JD}]$ is an input coefficient matrix describing the export structure of commodity k from overseas country p used in production of Japanese domestic commodity j_1, $\tilde{\mathbf{A}}_{32}^{(k)}[\, n^G \times n^{JD}]$ represents the export structure of commodity k from overseas country p supplied directly to Japanese final demand as import commodity j_2, and $\tilde{\mathbf{A}}_{33}^{(k)}[n^G \times n^G]$ represents international trade of overseas commodity k between overseas countries p and q. Vector $\mathbf{d}^{JD}[n^{JD} \times 1]$ consists of elements indicating the direct environmental burden per unit production of the Japanese commodities, and $\mathbf{i}^{JD(i_1 = \alpha)}[n^{JD} \times 1]$ is a vector with an element of unity solely for Japanese commodity $i_1 = \alpha$ and an element of zero for other commodities. $\mathbf{i}^G[n^G \times 1]$ is vector of which all of the elements are unity. $\mathbf{I}\left[(2n^{JD} + n^G) \times (2n^{JD} + n^G)\right]$ is the identity matrix. The symbol diag in eq 1 means diagonalization of the vector.

2.2. Economic, Energy, and Environmental Data Compilation.
To set the matrices $\mathbf{A}_{11}$ and $\tilde{\mathbf{A}}_{13}$ in eq 1, we used the same economic data as in our previous article.[29] The numbers of sectors n^{JD} and n^G in eq 2 are thus 406 and 230. One hundred and eleven foreign commodities ($k = 1...111$) were considered. With respect to the total domestic GHG emissions per unit production captured in vector $\mathbf{d}^{JD}$ and the total overseas GHG emissions embedded in international trade given by $\tilde{\mathbf{A}}_{31}^{(k)}$, $\tilde{\mathbf{A}}_{32}^{(k)}$, and $\tilde{\mathbf{A}}_{33}^{(k)}$, we also used the GHG emission data compiled in the same previous article.[29] With respect to individual GHGs, that is carbon dioxide (CO_2, both fuel-derived and nonfuel-derived), methane (CH_4), nitrous oxide (N_2O), perfluorocarbons (PFCs), hydrofluorocarbons (HFCs), and sulfur hexafluoride (SF_6), this study referred to the Embodied Energy and Emission Intensity Data for Japan Using Input-Output Tables (3EID)[4,10] for vector $\mathbf{d}^{JD}$ and the United Nation Framework Convention on Climate Change (UNFCCC) inventory,[33] International Energy Agency (IEA) data,[34] Enerdata,[35] the Emissions Database for Global Atmospheric Research (EDGAR) ver. 4.1,[36] and the Carbon Dioxide Information Analysis Center (CDIAC)[37] for matrices $\tilde{\mathbf{A}}_{31}^{(k)}$, $\tilde{\mathbf{A}}_{32}^{(k)}$, and $\tilde{\mathbf{A}}_{33}^{(k)}$. The global warming potentials for a 100-year time horizon defined in the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report[38] were applied to convert emissions of GHGs other than CO_2 into CO_2 equivalents.

As to energy consumption, vector $\mathbf{d}^{JD}$ was estimated by converting the energy consumption on a gross calorific value (GCV) basis provided in 3EID to consumption on a net calorific value (NCV) basis. Values for matrices $\tilde{\mathbf{A}}_{31}^{(k)}$, $\tilde{\mathbf{A}}_{32}^{(k)}$, and $\tilde{\mathbf{A}}_{33}^{(k)}$ were estimated using IEA data[34] and Enerdata.[35]
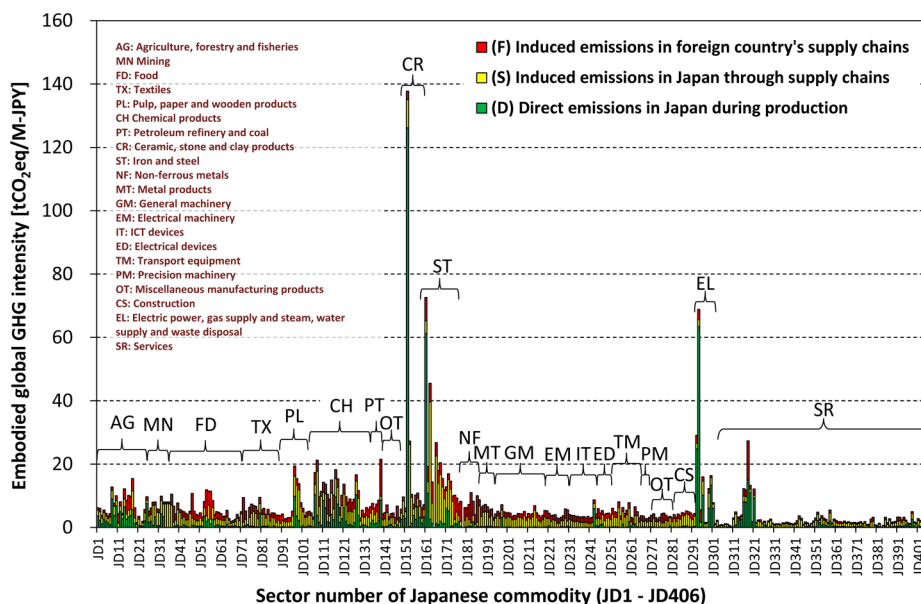
Figure 1. Embodied global GHG intensity of goods and services produced in Japan in 2005 and breakdown by emission category (direct emissions (D), induced emissions in Japan (S), induced emissions abroad (F)).

In the case of air pollutants (nitrogen oxide, NO_x, and sulfur oxide, SO_x), vector $\mathbf{d}^{JD}$ was calculated by multiplying the sectoral energy consumption data by fuel type reported in 3EID by the respective emission factors for each sector and fuel type. EDGAR was used to estimate matrices $\tilde{\mathbf{A}}_{31}^{(k)}$, $\tilde{\mathbf{A}}_{32}^{(k)}$, and $\tilde{\mathbf{A}}_{33}^{(k)}$. Whereas the energy consumption and emissions associated with international transportation can also be embedded in matrices $\tilde{\mathbf{A}}_{31}^{(k)}$, $\tilde{\mathbf{A}}_{32}^{(k)}$, and $\tilde{\mathbf{A}}_{33}^{(k)}$, these have not been included in the present study. Although the method to be used for national allocation of GHG emissions from bunker fuels for international transportation is not specified in the UNFCCC inventory reporting guidelines,[33] if such emissions were factored in, the values of embodied global GHG intensities (hereafter, global GHG intensities) would naturally increase, but the additional contribution to each commodity's global GHG intensity would be relatively insignificant.[39,26] The same would hold for embodied global energy intensity, too, because fuel consumption stands in direct proportion to CO_2 emissions. When it comes to NO_x and SO_x emissions, however, including those associated with international transportation would have a significant knock-on effect because the share of shipping air-pollutant emissions in the total is far greater.[4]

2.3. Uncertainties in Intensities of Embodied Global Environmental Burden Attributable to the Model Structure. The GLIO is designed to reduce the time and labor burdens of LCI data compilation with a global system boundary by using aggregated multiregional input–output structures for countries other than Japan, the economy of which is the specific focus here. However, this aggregated description affects the robustness of the global intensities derived in this way.[40−42] By means of Monte Carlo simulation,[41,43] we therefore estimated the coefficients of variation (%) $vc^{(i_1 = \alpha)}$ of the global intensities $e^{(i_1 = \alpha)}$ to quantify the uncertainties in the global intensities resulting from that description. Given space constraints, here too the procedures to determine $vc^{(i_1 = \alpha)}$ are set out in detail in the Supporting Information taking the case of total GHG emissions as an example.

3. RESULTS

3.1. Embodied Global GHG Intensities of Japanese Products. Figure 1 depicts the embodied global GHG intensities (global GHG intensity) [tCO_2eq/M-JPY] of commodities produced domestically in Japan in 2005, with the sector numbers (JD1−JD406) representing the commodities set out on the horizontal axis. The color composition of each emission indicates the phases in the commodity's supply chain during which GHG emissions occur: (D) Direct emissions in Japan during production, (S) induced emissions in Japan through the supply chain, and (F) induced emissions in foreign countries' supply chains. Here, the induced emissions mean emissions generated indirectly in the upstream supply chain behind the commodity's production. As Figure 1 shows, the global GHG intensities of the vast majority of sectors are below about 30 tCO_2eq/M-JPY. For most sectors, it is clearly the contributions of emission categories (S) and (F) that push global GHG intensity values upward, but the magnitude of these contributions varies among sectors.

The sector numbers and corresponding sector names and global GHG intensities as well as figures for the emission categories (D), (S), and (F) are listed in Table A2 of the Supporting Information. Given space constraints, here we restrict ourselves to describing the characteristics of the global GHG intensities; the sectoral intensities for the other environmental pressures considered are listed in Tables A1 and A3−A10 of the Supporting Information.

3.2. Sectors with the Most Characteristic Embodied Global GHG Intensity. *3.2.1. Sectors with the Highest Embodied Global GHG Intensity.* Table 1 presents the 10 sectors with the highest embodied global GHG intensity showing the respective contributions of (D), (S), and (F). The sector with by far the highest global GHG intensity is cement (JD152), followed by pig iron (JD161), on-site power generation (JD294), and crude steel (converters) (JD163). These are the only sectors with a global GHG intensity exceeding 30 tCO_2eq/M-JPY. With the exception of JD163, it is the high value of category (D) emissions, direct emissions in Japan, which engenders the high overall global GHG intensity. In the case of JD163, the

Table 1. Ten Japanese Domestic Products with the Greatest Embodied Global GHG Emission Intensity and the Shares of Direct Emissions, Induced Emissions in Japan, and Induced Emissions in Foreign Countries

rank	sector number and name	embodied global GHG intensity	(D) share of direct emissions in Japan	(S) share of induced emissions in Japan	(F) share of induced emissions in foreign country
		[t-CO$_2$eq/M-JPY]	[%]	[%]	[%]
1	JD152: cement	138	92	6	2
2	JD161: pig iron	72.6	84	6	10
3	JD294: on-site power generation	68.8	92	3	5
4	JD163: crude steel (converters)	45.5	6	82	13
5	JD293: electricity	29.1	85	6	9
6	JD318: ocean transport	27.3	52	2	46
7	JD153: ready-mixed concrete	27.3	1	95	4
8	JD166: hot rolled steel	26.8	4	80	16
9	JD139: coal products	21.5	40	6	54
10	JD108: industrial soda chemicals	21.2	18	66	16

production of JD161 induced in the supply chain is a key emission source, that is the global GHG intensity value is large because of the contribution of category (S) emissions, induced emissions in Japan. The global GHG intensities of ready-mixed concrete (JD153) and hot rolled steel (JD166) are also due largely to the share of category (S) emissions, contributing 95% and 80%, respectively. Whereas ocean transport (JD318) and coal products (JD139) have similar global GHG intensities to JD153 and JD166, these derive mainly from emission categories (D) and (F).

3.2.2. Sectors with the Highest Percentage Share of Induced Emissions in Foreign Countries. Table 2 identifies

Table 2. Ten Japanese Domestic Products with the Greatest Share of Induced Foreign Emissions in Their Embodied Global GHG Emission Intensity

rank	sector number and name	share of foreign emissions in embodied global GHG intensity [%]
1	JD183: rolled and drawn aluminum	86
2	JD186: other nonferrous metal products	83
3	JD72: feeds	82
4	JD56: vegetable oils and meal	76
5	JD178: other nonferrous metals	76
6	JD175: copper	75
7	JD38: processed meat products	75
8	JD185: nuclear fuels	75
9	JD47: flour and other grain milled products	72
10	JD295: gas supply	71

the commodities with the highest percentage share of category (F) emissions (induced emissions in foreign countries) in their global GHG intensity. At the top of the list is rolled and drawn aluminum (JD183), with 86% of global GHG intensity due to overseas emissions, indicating that production of aluminum products in Japan induces substantial emissions abroad. This sector is followed by other nonferrous metal products (JD186) with 83%, animal feed (JD72) with 82%, vegetable oils and meal (JD56) with 76%, and other nonferrous metals (JD178) with 76%. These sectors, too, cause substantial emissions in global supply chains through consumption of metal resources and crops for animal feed and forage.

3.2.3. Sectors with the Greatest Difference from the Embodied GHG Intensity under the Domestic Technology

Table 3. Ten Japanese Domestic Products with the Greatest Difference between the Embodied Global GHG Emission Intensity Calculated in This Study and That Calculated under the Domestic Technology Assumption

rank	sector number and name	difference of GHG emissions with use of the domestic technology assumption [%]
1	JD183: rolled and drawn aluminum	−66
2	JD11: seeds and seedlings	−57
3	JD47: flour and other grain mill products	−52
4	JD90: timber	−52
5	JD72: feeds	−51
6	JD186: other nonferrous metal products	−49
7	JD56: vegetable oils and meal	−48
8	JD277: tatami (straw matting) and straw products	−47
9	JD185: nuclear fuels	−44
10	JD54: starch	−42

Assumption. An embodied GHG intensity under the domestic technology assumption (DTA) means that the emissions associated with imports are assumed to be the same as those of equivalent domestic products (for calculation of this intensity, see the Supporting Information). The commodities with the greatest difference between the global GHG intensity and intensity under DTA are presented in Table 3. With DTA, the greatest underestimation of sector, −66%, is for rolled and drawn aluminum (JD183). The main reason is that this sector induces large overseas emissions for aluminum primary smelting, but that these emissions are largely avoided under the DTA, for although Japan carries out secondary aluminum smelting for recycling, there is no domestic primary aluminum smelting, whereas it is this process that requires major inputs of electricity. Calculating with DTA thus assumes the use of secondary smelting technology for primary smelting leading to a major under-estimation for the sector.

This sector is followed by several food- and agriculture-related sectors such as seeds and seedlings (JD11) (−57%), flour and other grain mill products (JD47) (−52%), timber (JD90) (−52%), and Feeds (JD72) (−51%). In contrast, in certain sectors use of domestic data may lead to overestimation of global GHG emissions, as with tea and roasted coffee (JD69) (14%), and plasticizers (JD120) (3.4%).

3.2.4. Sectors with the Greatest Uncertainty in Embodied Global GHG Intensity. Table 4 presents the top 10 sectors with a

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Table 4. Ten Japanese Domestic Products with the Greatest Coefficient of Variation of Their Embodied Global GHG Emission Intensity

rank	sector number and name	coefficient of variation of embodied global GHG intensity [%]
1	JD11: seeds and seedlings	22.1
2	JD318: ocean transport	16.8
3	JD262: aircraft repair	16.6
4	JD56: vegetable oils and meal	16.2
5	JD138: petroleum refinery products (incl. greases)	15.7
6	JD72: feeds	15.6
7	JD54: starch	14.6
8	JD47: flour and other grain mill products	13.8
9	JD38: processed meat products	11.7
10	JD342: image information production and distribution	10.4

particularly large coefficient of variation. Heading the list is seeds and seedlings (JD11) (22%). The global GHG intensity of this sector was estimated as 4.36 tCO$_2$eq/M-JPY, so that with its coefficient of variation of 22% the true emissions lie between $4.36 \times (1 + 0.22) = 5.32$ and $4.36 \times (1-0.22) = 3.40$ tCO$_2$/M-JPY. This is followed by ocean transport (JD318) (17%), aircraft repair (JD262) (17%), vegetable oils and meal (JD56) (16%), and petroleum refinery products (incl. greases) (JD138) (16%).

3.3. Overall Trends of the Structural Characteristics of Embodied Global GHG Intensity. *3.3.1. Trend of Magnitude of Embodied Global GHG Intensity.* As a first step, we examined the relationship between the global GHG intensity and the key economic indicators (domestic output and value added) of each sector. Part a of Figure 2 (an enlarged version of which is included in the Supporting Information) is a scatter diagram in which the horizontal axis represents the percentage share of each sector in total Japanese domestic output and the vertical axis the global GHG intensity (tCO$_2$eq/M-JPY). From this figure, it is immediately apparent that the data points are essentially distributed transversely, and the correlation coefficient is as low as −0.083. There is thus no linear relationship between the level of domestic output and embodied emission intensity. However, the Spearman rank correlation coefficient or Spearman's ρ of the variables is −0.238 pointing to a decreasing monotonic relationship.

Part b of Figure 2 shows the relationship between the value added ratio (M-JPY/M-JPY) of each sector (the horizontal axis) and its global GHG intensity (tCO$_2$-eq/M-JPY) (the vertical axis). From this figure, it is apparent that the global GHG intensity gradually decreases with increasing value added ratio. The correlation coefficient is −0.293 reflecting a weakly negative correlation. Spearman's ρ of the variables, −0.399, means a decreasing monotonic relationship. Because value added is a constituent element of total domestic output, the greater its ratio, the lower the relative costs of intermediate inputs such as raw materials. These lower costs of intermediate inputs are presumably associated with lower GHG emissions, so that the higher the value added ratio of a commodity, the lower its embodied emission intensity.

However, part c of Figure 2 presents the relationship between the share (%) of the sector's direct emissions in total Japanese emissions (the horizontal axis) and its global GHG intensity (tCO$_2$eq/M-JPY) (the vertical axis). As the figure shows, as the

share of direct emission in Japan increases, so too does the global GHG intensity. The correlation coefficient is 0.403, signifying a positive correlation. Spearman's ρ of the variables, 0.359, shows an increasing monotonic relationship. Referring to Figure 1, among sectors with a higher global GHG intensity the relatively high contribution of direct emissions (category (D)) can indeed be confirmed for many sectors. Higher overall emissions are thus a factor pushing up unit direct emissions, as reflected in the trend of part c of Figure 2.

3.3.2. Trend of Induced Foreign GHG Emissions in Embodied Global GHG Intensity. This article focuses on the relationship between the induced foreign GHG emissions in the global GHG intensity and the emission characteristics (direct emissions and induced domestic emissions) of each sector. Part d of Figure 2 is a scatter diagram with the horizontal axis representing the volume (tCO$_2$eq/M-JPY) of the unit direct emissions (D) of each sector and the vertical axis representing the induced foreign emissions (F) (tCO$_2$eq/M-JPY) component of the global GHG intensity. Although the trend is only slight, as the unit direct emission increases so too does the induced foreign emission. In other words, it appears that sectors with higher unit direct emissions in Japan do not necessarily avoid similar or greater emissions overseas. The correlation coefficient is 0.192, signifying a weakly positive correlation, but too weak to establish any definite linear relationship. Spearman's ρ of the variables, 0.365, confirms an increasing monotonic relationship.

Part e of Figure 2 portrays, for each sector, the relationship between the induced domestic emission (S) (tCO$_2$eq/M-JPY) component of the global GHG intensity (the horizontal axis) and the induced foreign emission (F) component (tCO$_2$eq/M-JPY) (the vertical axis). The correlation coefficient is 0.224 indicating a positive correlation that is stronger than in the case of direct emissions described in the previous section. Spearman's ρ of the variables is 0.522 signifying an increasing monotonic relationship.

The input coefficient describing the production process of each sector includes inputs of imported commodities. For this reason, if production activities of other sectors are induced in the production supply chainthen the input amounts of imported commodities are simultaneously increased. Because GHG are emitted by almost all sectors, the same characteristics will appear even if production activity is expressed based on GHG emissions. A sector inducing greater indirect GHG emissions within the country thus tends to induce greater emissions abroad, too.

3.3.3. Trend of Difference in Embodied GHG Intensity under the Domestic Technology Assumption. Part f of Figure 2 is a scatter diagram with the horizontal axis representing the share of induced foreign emissions (F) in the global GHG intensity of each sector and the vertical axis representing the difference (%) between the global GHG intensity calculated in the present study and the embodied GHG intensity derived under the DTA. If the difference is negative, then the global GHG intensity derived using GLIO is greater than the intensity under the DTA; if it is positive, the opposite holds. The coefficient of correlation between the share of emissions abroad and the absolute value of the difference is 0.828 signifying a strong correlation. Spearman's ρ of the variables is 0.813 signifying a markedly increasing monotonic relationship. In other words, even if Japanese domestic technology is assumed for imported commodities, it is unable to accurately duplicate the features of the GHG emissions of imported commodities. The difference from the intensity calculated under the DTA is particularly striking in
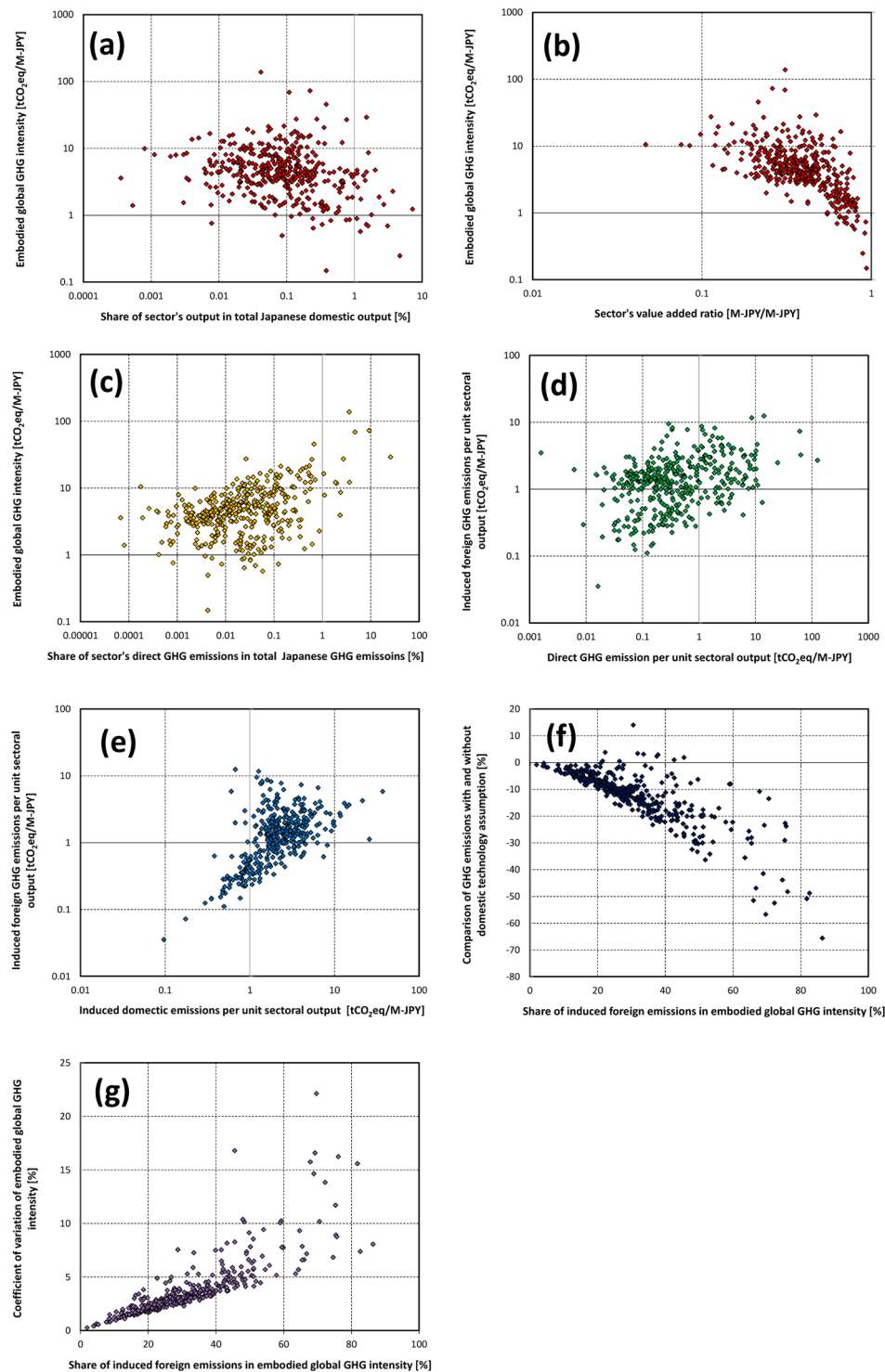
Figure 2. (a) Relation between the share of sector's output in total Japanese output and embodied global GHG intensity, (b) relation between sector's value added ratio and embodied global GHG intensity, (c) relation between sector's direct GHG emission and embodied GHG intensity, (d) relation between direct GHG emission per unit sectoral output and induced foreign GHG emission per unit sectoral output, (e) relation between induced domestic emission per unit sectoral output and induced foreign GHG emission per unit sectoral output, (f) relation between share of induced foreign emissions in embodied global GHG intensity and comparison of GHG emissions with and without domestic technology assumption, (g) relation between share of induced foreign emissions in embodied global GHG intensity and coefficient of variation of embodied global GHG intensity.

those sectors showing the highest share of induced foreign emissions associated with imported commodities.

3.3.4. Trend of Uncertainty in Embodied Global GHG Intensity. In part g of Figure 2, the horizontal axis represents the percentage share (%) of overseas (category (F)) emissions in the global GHG intensity and the vertical axis the coefficient of

variation (%). As is readily apparent, an increase in the share of overseas emissions in the global GHG intensity tends to increase the coefficient of variation. The correlation coefficient is 0.821 indicating a strong positive correlation. Spearman's ρ of the variables is 0.920, a definite sign of an increasing monotonic relationship. However, although the maximum share of overseas

emissions is 86% (Table 2), the maximum value of the coefficient of variation is 22% while remaining below 5% in many sectors. No overall linear relation can consequently be established between the share of induced foreign emissions and the coefficient of variation (magnitude of uncertainty).

In addition, the impact of sectoral aggregation on the uncertainty of global GHG intensities was analyzed. Table S1 of the Supporting Information summarizes the weighted average (WA) of the global intensities aggregated to 21 broad commodity categories using a weighting coefficient based on the total domestic output of each sector. The table also shows the minimum and maximum global GHG intensity recorded in each category. Because the two-capital-letter codes used for the commodity categories in Table S1 are the same as those in Figure 1, it can readily be seen from the latter which categories are associated with which global intensities. The range columns in Table S1 of the Supporting Information show the values obtained by dividing the minimum and the maximum by the weighted average and expressing this as a percentage, and this may be taken as the range in which the weighted average is valid. The greater the similarity between the global GHG intensities within a given broad commodity category, the smaller this range becomes. This range is thus an index of the similarity in global intensity within the broad commodity category.

The range of the global GHG intensity of ICT devices (IT) and precision machinery (PM) is relatively narrow: 85%−112% and 90%−119% respectively, which indicates broad similarity in the global GHG intensities of the sectors belonging to these two categories. However, certain categories such as services (SR) and ceramic, stone and clay products (CR) exhibit a far wider range: 5%−1350% and 32%−726%, respectively. In terms of this range, 10 categories have a lower bound of less than 50% (half the weighted average) and 9 categories have an upper bound of more than 200% (twice the weighted average). These results are broadly similar to the spread of global GHG intensities to emerge from process-based LCA on the same sector categories as defined here in an input−output table.[44]

The range of induced foreign emissions in the global GHG intensity was also computed. Similarly to above, ICT devices (IT) and precision machinery (PM) again show a relatively narrow range in this respect of 83%−115% and 69%−123%, respectively. Here, there is indeed similarity with the situation for overall global GHG intensity. At the same time though, certain categories such as electric power, gas supply and steam, water supply, and waste disposal (EL), corresponding to utilities, exhibit an expanded range of 39%−710% with regard to the share of foreign emissions. For eight commodity categories, the lower bound of the range is less than 50%, whereas for six categories the upper bound is over 200%. There are thus fewer categories with a variation extending down to less than half or up to more than twice the weighted average than in the case of overall global GHG intensity. This implies that the emission structure of the global GHG intensity of products belonging to the same broad category do not exhibit any great similarity.

Finally, we also calculated the range of the coefficient of variation of the global intensity. In this respect, IT showed a narrower range of 75%−130%, whereas PM showed a wider range of 59%−249%. The lower bound of the range is less than 50% for nine categories, whereas the upper bound is over 200% for 11 categories leading to the conclusion that uncertainty of global GHG intensity tends to increase with sectoral aggregation because there is even less similarity in the uncertainty in global

GHG intensity of products belonging to the same commodity category than in the case of emission structure just described.

4. DISCUSSION

4.1. Implications of the Characteristics of Embodied Global GHG Intensities for Use in LCA. *4.1.1. Commodities with a High Embodied Global GHG Intensity.* For the purposes of input−output LCA and hybrid LCA, if the LCA practitioner knows the 2005 producer price (M-JPY) of the commodity under study this price can be multiplied by the global intensity (tCO$_2$eq/M-JPY) of that commodity to obtain its cradle-to-gate LCI with respect to GHG (tCO$_2$eq) based on a global system boundary. The producer price can be estimated from the physical quantity (e.g., kilogram) of the commodity and its unit price (e.g., M-JPY/kg) in 2005. In input−output LCA and hybrid LCA on manufacturing processes and technologies with input of high global-GHG-intensity commodities, such as presented in Table 1, or with lower value added (but no relation to sectoral output level: parts a and b of Figure 2), the accuracy of the price or physical amounts of these commodities thus has a significant bearing on the life cycle emissions calculated and, consequently, on the overall reliability of the LCI result. In such cases, the LCA practitioner should therefore take extra care in quantifying prices and physical quantities giving due consideration to year-to-year differences in prices and/or technologies.

In process LCA, such high-global GHG intensity commodities should be identified in the screening phase as deserving particularly high priority in terms of collecting detailed process data. For most such commodities, it is direct emissions that are the main contributor to the high global GHG intensity (part c of Figure 2), and the on-site emissions occurring at the commodity's production site should therefore be given greater emphasis than those associated with its global supply chain.

4.1.2. Commodities with a Large Share of Foreign Emissions and Use of the Domestic Technology Assumption. A commodity with a high proportion of overseas emissions generates large GHG emissions in the foreign supply chain associated with the imported materials and services used in the domestic supply chain in Japan. For commodities with a large share of foreign emissions, as presented in Table 2, the LCA practitioner should give priority to collecting process and emission data on the imports used in the supply chain. In process LCA, because commodities with large domestic emissions (both direct and indirect) tend to show large foreign emissions (parts d and e of Figure 2) due effort should be made to identify the foreign emissions associated with such commodities.

However, data on processes and emissions in foreign countries are often scarce as well as costly to retrieve. Hence, in the case of such commodities, too, input−output LCA and hybrid LCA using the data described as a result of this study have major benefits over process LCA, which generally has no option but to ignore the foreign emissions associated with a commodity for reasons of cost and data availability.

For such commodities, an alternative to process LCA is to apply domestic (Japanese) process and emission data for imported materials and services. This substitution assumes that the production technology of an imported commodity is equivalent to that of the corresponding domestic commodity. If an LCA of the commodity using domestic emission data rather than those of the imports in question yields a similar result to an LCA, that does give due consideration to global supply chain emissions, and then the process LCA of the commodity can

provide a rough estimate of its global GHG emissions using only domestic data, which are readily obtainable.

From the comparison of the global GHG intensities with the intensities under the DTA, this study has confirmed that, with relatively few exceptions, presented in Table 3, most sectors show differences between about −40% and 20% (part f of Figure 2). If an LCA practitioner defines what degree of under/overestimation is acceptable for the global GHG of a commodity, then use of domestic data as a surrogate for the data on imported commodities used in the supply chain might be deemed a suitable alternative in a process LCA.[45]

4.1.3. Consideration of Uncertainty in Embodied Global GHG Intensity. Although a simplified method was used to calculate global GHG intensities, the majority of sectors show a coefficient of variation of less than 10% in their global GHG intensity, as presented in part g of Figure 2, and can thus be deemed well amenable to LCI data based on an input−output analysis. Only relatively few commodities, shown in Table 4, exhibit greater variation. Use of these data thus permits simple estimation of the uncertainty in the results of applying the global GHG intensities obtained in this study to yield an LCI. As Table S1 of the Supporting Information shows, however, it should be noted that this uncertainty in global GHG intensity increases markedly if sectors are aggregated.

In input−output LCA, the coefficient of variation of the sector can itself be interpreted as being the uncertainty of the LCI. With hybrid LCA and particularly tiered hybrid LCA,[1] assuming no correlation among the coefficients of variation in the sectors, the possible range of each intensity is calculated from the coefficients of variation and the emissions are calculable for the highest global GHG intensity value and for the lowest. This enables estimation of the range of uncertainty of emissions through the connection with input−output analysis in hybrid LCA.

In this study, however, the uncertainty was estimated using the input structure of Japan's domestic commodities, which does not reflect the characteristics of commodities produced elsewhere (particularly energy and mineral resources). In addition, supply chains that enjoy a geographical advantage to eastern Asia, including China as a high carbon emitter,[46−48] start weighing in on the results, implying a possible overestimation of uncertainty. At the same time, estimating the variation in the input co-efficients of overseas sectors in the GLIO model using Monte Carlo simulation rested on the extreme assumption that each country except for Japan has a production structure in which it produces only one type of commodity (for details, Supporting Information). Consequently, this methodology may also engender an overestimate of uncertainty. However, the GLIO model aggregates foreign commodities into 111 types leading to a potential underestimate of uncertainty.[40,42]

ASSOCIATED CONTENT

Ⓢ Supporting Information

Enlarged versions of the constituent graphs of Figure 2, additional descriptions of methodologies of all the sectoral global intensities (energy consumption, GHGs and air pollutant emissions) of Japanese products in PDF and Unicode Text (.txt) formats. It also describes further discussion on policy implication and limitations of the global intensities, and methodological applicability to other countries of the GLIO model. This material is available free of charge via the Internet at http://pubs.acs.org.

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REFERENCES

(1) Suh, S.; Lenzen, M.; Treloar, G. J.; Hondo, H.; Horvath, A.; Huppes, G.; Jolliet, O.; Klann, U.; Krewitt, W.; Moriguchi, Y.; Munksgaard, J.; Norris, G. System boundary selection in life-cycle inventories using hybrid approaches. *Environ. Sci. Technol.* **2004**, *38* (3), 657−664.

(2) Suh, S. Functions, commodities and environmental impacts in an ecological-economic model. *Ecological Economics* **2004**, *48* (4), 451−467.

(3) ecoinvent. http://www.ecoinvent.ch/

(4) Nansai, K.; Moriguchi, Y.; Tohno, S. Compilation and application of Japanese inventories for energy consumption and air pollutant emissions using input-output tables. *Environ. Sci. Technol.* **2003**, *37* (9), 2005−2015.

(5) Lave, L. B.; Cobasflores, E.; Hendrickson, C. T.; Mcmichael, F. C. Using Input-Output-Analysis to Estimate Economy-Wide Discharges. *Environ. Sci. Technol.* **1995**, *29* (9), A420−A426.

(6) Suh, S.; Huppes, G. Missing inventory estimation tool using extended input-output analysis. *Int. J. Life Cycle Ass.* **2002**, *7* (3), 134−140.

(7) Hendrickson, C.; Horvath, A.; Joshi, S.; Lave, L. Economic input-output models for environmental life-cycle assessment. *Environ. Sci. Technol.* **1998**, *32* (7), 184a−191a.

(8) CEDA CEDA: Comprehensive Environmental Data Archive. http://www.cedainformation.net/home.asp

(9) EIO-LCA Economic Input-Output Life Cycle Assessment (EIO-LCA). http://www.eiolca.net/

(10) *3EID Embodied Energy and Emission Intensity Data for Japan Using Input-Output Tables (3EID)*; Center for Global Environmental Research, National Institute for Environmental Studies: Ibaraki, 2002.

(11) ISA, The University of Sydney. Balancing Act: A Triple bottom line analysis of the Australian economy. http://www.isa.org.usyd.edu.au/publications/balance.shtml#accessing

(12) DB2010 International Open Workshop "Wolrdwide efforts on LCA Database" & International Stakeholder Engagement Meeting "Towards Global Guidance for LCA Databases". http://www.sntt.or.jp/DB2010/

(13) Weidema, B. P. In *The ecoinvent database - linking to the global market*, The 9th International Conference on EcoBalance (EcoBalance2010), Tokyo, Japan, November 9−12, 2010; Tokyo, Japan, 2010; pp 338-339.

(14) Kobayashi, K.; Tahara, K.; Wei, B. In *Method developed for simplified inventory-data estimation of foreign-made products*, The 9th International Conference on EcoBalance (EcoBalance2010), Tokyo, Japan, November 9−12, 2010; Tokyo, Japan, 2010; pp 346-349.

(15) Leontief, W.; Duchin, F.; Szyld, D. B. New approaches in economic-analysis. *Science* **1985**, *228* (4698), 419−422.

(16) Lenzen, M.; Pade, L.-L.; Munksgaard, J. CO_2 multipliers in multi-region input-output models. *Econ. Syst. Res.* **2004**, *16* (4), 11.

(17) Daniels, P. L.; Lenzen, M.; Kenway, S. J. The ins and outs of water use - a review of multi-region input-output analysis and water footprints

for regional sustainability analysis and policy. *Econ. Syst. Res.* **2011**, *23* (4), 353−370.

(18) Wiedmann, T. O.; Suh, S.; Feng, K. S.; Lenzen, M.; Acquaye, A.; Scott, K.; Barrett, J. R. Application of hybrid life cycle approaches to emerging energy technologies - the case of wind power in the UK. *Environ. Sci. Technol.* **2011**, *45* (13), 5900−5907.

(19) Acquaye, A. A.; Wiedmann, T.; Feng, K. S.; Crawford, R. H.; Barrett, J.; Kuylenstierna, J.; Duffy, A. P.; Koh, S. C. L.; McQueen-Mason, S. Identification of 'carbon hot-spots' and quantification of GHG intensities in the biodiesel supply chain using hybrid LCA and structural path analysis. *Environ. Sci. Technol.* **2011**, *45* (6), 2471−2478.

(20) Davis, S. J.; Caldeira, K. Consumption-based accounting of CO_2 emissions. *Proc. Natl. Acad. Sci. U.S.A.* **2010**, *107* (12), 5687−5692.

(21) Hertwich, E. G.; Peters, G. P. Carbon footprint of nations: A global, trade-linked analysis. *Environ. Sci. Technol.* **2009**, *43* (16), 6414−6420.

(22) Nakano, S.; Okamura, A.; Sakurai, N.; Suzuki, M.; Tojo, Y.; Yamano, N. *The Measurement of CO_2 Embodiments in International Trade: Evidence from the Harmonised Input-Output and Bilateral Trade Database*; OECD: Paris, 2009.

(23) Wiedmann, T.; Wood, R.; Minx, J. C.; Lenzen, M.; Guan, D. B.; Harris, R. A carbon footprint time series of the UK - Results from a multi-region input-output model. *Econ. Syst. Res.* **2010**, *22* (1), 19−42.

(24) Baiocchi, G.; Minx, J. C. Understanding changes in the UK's CO_2 emissions: A global perspective. *Environ. Sci. Technol.* **2010**, *44* (4), 1177−1184.

(25) Peters, G. P.; Minx, J. C.; Weber, C. L.; Edenhofer, O. Growth in emission transfers via international trade from 1990 to 2008. *Proc. Natl. Acad. Sci. U.S.A.* **2011**, *108* (21), 8903−8908.

(26) Peters, G. P.; Andrew, R.; Lennox, J. Constructing an environmentally-extended multi-regional input-output table using the GTAP database. *Econ. Syst. Res.* **2011**, *23* (2), 131−152.

(27) Hertwich, E. G. The life cycle environmental impacts of consumption. *Econ. Syst. Res.* **2011**, *23* (1), 27−47.

(28) Wiebeab, K. S.; Brucknerc, M.; Giljumc, S.; Lutza, C. Calculating Energy-Related CO_2 Emissions Embodied in International Trade Using a Global Input-Output Model. *Econ. Syst. Res.* **2012**, *24* (2), 113−139.

(29) Nansai, K.; Kagawa, S.; Kondo, Y.; Suh, S.; Nakajima, K.; Inaba, R.; Oshita, Y.; Morimoto, T.; Kawashima, K.; Terakawa, T.; Tohno, S. Characterization of economic requirements for a "carbon-debt-free country". *Environ. Sci. Technol.* **2012**, *46* (1), 155−163.

(30) Lenzen, M.; Kanemoto, K.; Geschke, A.; Moran, D.; Ugon, P. M. J.; Wood, R.; Yu, T. A global multi-region input-output time series at high country and sector detail. In *18th International Conference on Input-Output Analysis*, Sydney, 2010; p 30.

(31) Lenzen, M.; Moran, D.; Kanemoto, K.; Foran, B.; Lobefaro, L.; Geschke, A. International trade drives biodiversity threats in developing nations. *Nature* **2012**, *486* (7401), 109−112.

(32) Nansai, K.; Kagawa, S.; Kondo, Y.; Suh, S.; Inaba, R.; Nakajima, K. Improving the completeness of product carbon footprints using a global link input-output model: The case of Japan. *Econ. Syst. Res.* **2009**, *21* (3), 267−290.

(33) UNFCCC GHG Data. http://unfccc.int/2860.php

(34) IEA *CO_2 emissions from fuel combustion 1971- 2005*; International Energy Agency: Paris, 2007.

(35) Enerdata Enerdata. http://www.enerdata.net/

(36) EDGAR, The Emissions Database for Global Atmospheric Research (EDGAR). In European Commission - JRC Joint Research Centre: 2011.

(37) CDIAC Carbon Dioxide Information Analysis Center. http://cdiac.ornl.gov/ (04/15),

(38) Forster, P., V.; Ramaswamy, P.; Artaxo, T.; Berntsen, R.; Betts, D. W.; Fahey, J.; Haywood, J.; Lean, D. C.; Lowe, G.; Myhre, J.; Nganga, R.; Prinn, G.; Raga, M.; Schulz; Dorland, R. V. Changes in atmospheric constituents and in radiative forcing. In: Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change; Solomon, S., Qin, D.; Manning, M.; Chen, Z.; Marquis, M.; Averyt, K. B.;

M. Tignor Miller, H.L., eds; Cambridge University Press: Cambridge, United Kingdom and New York, NY, USA, 2007.

(39) Weber, C. L.; Matthews, H. S. Food-miles and the relative climate impacts of food choices in the united states. *Environ. Sci. Technol.* **2008**, *42* (10), 3508−3513.

(40) Su, B.; Huang, H. C.; Ang, B. W.; Zhou, P. Input-output analysis of CO_2 emissions embodied in trade: The effects of sector aggregation. *Energ. Econ.* **2010**, *32* (1), 166−175.

(41) Lenzen, M.; Wood, R.; Wiedmann, T. Uncertainty analysis for multi-region input-output models - a case study of the UK's carbon footprint. *Econ. Syst. Res.* **2010**, *22* (1), 43−63.

(42) Lenzen, M. Aggregation versus disaggregation in input-output analysis of the environment. *Econ. Syst. Res.* **2011**, *23* (1), 73−89.

(43) Wiltinga, H. C. Sensitivity and Uncertainty Analysis in MRIO Modelling; Some Empirical Results with Regard to the Dutch Carbon Footprint. *Econ. Syst. Res.* **2012**, *24* (2), 147−171.

(44) Majeau-Bettez, G.; Strømman, A. H.; Hertwich, E. G. Evaluation of process- and input-output-based life cycle inventory data with regard to truncation and aggregation issues. *Environ. Sci. Technol.* **2011**, *45*, 10170−10177.

(45) Andrew, R.; Peters, G. P.; Lennox, J. Approximation and regional aggregation in multi-regional input-output analysis for national carbon footprint accounting. *Econ. Syst. Res.* **2009**, *21* (3), 311−335.

(46) Minx, J. C.; Baiocchi, G.; Peters, G. P.; Weber, C. L.; Guan, D.; Hubacek, K. A carbonizing dragon: China's fast growing CO_2 emissions revisited. *Environ. Sci. Technol.* **2011**, *45* (21), 9144−9153.

(47) Guan, D.; Peters, G. P.; Weber, C. L.; Hubacek, K. Journey to world top emitter: An analysis of the driving forces of China's recent CO(2) emissions surge. *Geophys. Res. Lett.* **2009**, 36.

(48) Weber, C. L.; Peters, G. P.; Guan, D.; Hubacek, K. The contribution of Chinese exports to climate change. *Energy Policy* **2008**, *36* (9), 3572−3577.

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There was an error in the second paragraph of the Methods and Data section in the version of this paper published August 10, 2012. The correct version published August 21, 2012.

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