Structural Change and the Environment

A Case Study of China's Production Recipe and Carbon Dioxide Emissions

Jun Lan, Manfred Lenzen, Erik Dietzenbacher, Daniel Moran, Keiichiro Kanemoto, Joy Murray, and Arne Geschke

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Summary

We use the input-output tables in constant prices extended with carbon dioxide (CO_2) emissions for examining the development of China, a country undergoing rapid growth. We undertake this empirical analysis in terms of a new and therefore rarely applied methodology: instead of average coefficients characterizing the average (old) technology operating throughout a particular reporting year, we calculate marginal coefficients—in monetary and CO_2 terms—that capture the additional (new) technology installed after that year. Marginal coefficients are increasingly recommended in the literature for applications such as consequential life cycle assessment, where they are supposed to lead to more realistic results, especially in prospective analyses. Our work provides a first, broad overview about the magnitude and distribution of these coefficients across recent years in China's rapidly growing economy for which marginal coefficients could be expected to differ greatly from average coefficients. We find that (1) marginal coefficients can differ substantially from average coefficients, thus lending support to the need expressed in the literature for coining consequential life cycle assessment (LCA) and similar prospective assessment in marginal rather than average terms; (2) marginal CO_2 emissions coefficients differ more from their average counterparts than marginal monetary coefficients, showing that for China, within-sector technological solutions to emissions abatement have played a more important role than the reorganization of supply structures; and (3) there exists considerable scatter and variation of marginal coefficients across years, which to a certain extent precludes the identification of clear temporal and sectoral trends.

Introduction

Technological change stimulates economic growth, but it also has a bearing on environmental impacts. If a stimulus to the economy leads to increasing emissions, such change will be a double-edged sword: new technologies and new production recipes can, but do not necessarily result in cleaner production. This is particularly true for economies under recently advancing economic growth (e.g., Brazil, Russia, India, and China). Any change in such countries has a significant bearing on global emissions and climate change trajectories (Guan et al. 2008; Peters et al. 2007; Wachsmann et al. 2009).

Address correspondence to: Jun Lan, University of Sydney, Integrated Sustainability Analysis, School of Physics A28, University of Sydney, Sydney, New South Wales 2006, Australia. *Email*: junlan@physics.usyd.edu.au

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Background

Technological and structural change has been monitored with the help of input-output tables (IOTs) (Azid 2002; Nielsen and Weidema 2001; Sato and Ramachandran 1980; Sawyer 1992). Indeed, input-output theory provides for a so-called matrix of input coefficients (Leontief 1966). These coefficients characterize the average technology installed, and the average input structure operating throughout the reporting year of the IOT. A time series of such matrices essentially traces the evolution of the production recipe of an economy over time. Another variant of coefficients, so-called marginal input coefficients, describe the incremental inputs necessary for the generation of an additional unit of gross output (Tilanus 1967).

Within the input-output discipline there is growing awareness of the need for different sets of data and different methodologies if change-oriented (prospective) environmental impacts of technological change in growing economies are to be estimated instead of descriptive (retrospective) impacts of existing technology. The input-output literature contains many examples of studies where average input coefficients are used to quantify the prospective impacts of new technologies, additional plants, or generally an altered economic structure. A somewhat unrealistic assumption in such applications is that the average economic structure present throughout the reporting year of the IOT is recruited for the production of those new plants (Hamilton and Pongtanakorn 1983). In reality, average input coefficients are likely to change throughout the current year through price variations, wage and salary progressions, and technology changes alike (Sawyer 1992). Thus the average input coefficients fail to indicate structural shifts in current economic activities (Azid 2002). Studies that have an explicit prospective focus would benefit from the use of marginal input coefficients that better reflect the most recent technological changes taking place (Finnveden and Moberg 2001; Tillman 2000).

A few decades ago, Middelhoek (1970) suggested that the use of marginal input coefficients instead of average input coefficients would permit the use of IOTs for medium-range planning. He argued that marginal input coefficients were not only stable over time, but could also be used in the same elegant way of conventional input-output analysis (IOA). Sato and Ramachandran (1980) pointed out that changes of coefficients revealed by IOA can be an indication of technical changes and their causes. Similarly Hamilton and Pongtanakorn (1983) showed that a Leontief matrix based on marginal input coefficients can be inverted and then used to describe the structural changes in an economy caused by an external impact.

Technological and structural change must also be seen as facilitating changes in resource use and environmental impacts. One of the most commonly used tools for assessment of prospective environmental impacts (Ekvall et al. 2007) is life cycle assessment (LCA), which is aimed at quantifying the resources used and the environmental impacts caused throughout a product's life cycle, that is, from raw material acquisition, to production and use phases, to waste management (ISO 2006). Based on pioneering work in the 1970s (Bullard et al. 1978), LCA has recently been operationalized in combination with IOA (Guinée et al. 2010; Heijungs and Suh 2002; Suh 2004a; Suh and Huppes 2005; Suh et al. 2003). The possibility of combining process information and IOA at different resolutions in a consistent framework offers a great advantage for both IOA and LCA practitioners (Nakamura et al. 2007).

There exist two methodological streams in LCA: attributional and consequential LCA,[1] depending on whether the LCA is used for descriptive (attributional) or change-oriented (consequential) studies. Attributional LCA is characterized by its ex post focus on describing the environmentally relevant physical flows during the life cycle of a product or process. Consequential LCA is defined by its aim to describe how environmentally relevant flows will change in response to small changes in the production structure of an economy. "Small" in this context means small enough so that it does not alter the overall production structure of the economy. In mathematical parlance, such changes are often called "marginal." Marginal changes can arise out of decisions to create, expand, or otherwise alter, for example, a specific industrial plant, transport infrastructure, or health and education facility. As stated by several scholars (Ekvall et al. 2005; Lundie et al. 2007; Weidema 2003), consequential LCA is more relevant for decision making, and some attempts have been made to illustrate its applicability.[2]

The confluence of IOA and LCA offers new ground to be explored using marginal input coefficients for consequential LCA.[3] Nielsen and Weidema (2001) agree that the introduction of dynamic and market-based (marginal) input coefficient modeling to IOA would be an important improvement for (prospective) decision support and a topic for future research. Marginal input coefficient models are more relevant for what-if scenario analysis than are average input coefficients (Azid 2002; Nielsen and Weidema 2001).

Motivation and Novelty

The motivation for the study described in this article is as follows:

- LCA can and is being used to characterize the environmental consequences of prospective investment in technologies, and to support strategic technological choice (Sandén and Karlström 2007). Therefore LCA can play an important role in steering the future technological and structural trajectories of rapidly growing, large economies toward environmentally benign outcomes.
- The variant most relevant for prospective studies is consequential LCA, which in turn requires information about marginal structural change, which—in principle—can be provided by input-output tables in a standard form, at a comprehensive sector and country coverage.
- As a result, the routine and timely provision in published IOTs of marginal coefficients along with the conventional average coefficients could greatly improve the relevance of

LCA under circumstances of rapid and significant growth, for example, in China.

Significant progress has been made in the use of marginal input coefficients for consequential LCA. However, as far as we are aware, there exists no systematic review of these coefficients and their stability on the basis of existing input-output data. Our work seeks to fill this knowledge gap by enumerating and comparing marginal and average input coefficients for a range of periods for the example of China. We will examine whether the empirical evidence on marginal input coefficients is sufficiently sound to foster our understanding of structural change occurring in China's rapidly growing economy.

We extend the strict definition of the term "marginal" in that we allow our marginal coefficients to refer to multiyear periods in order to be able to examine the structure of changes in intermediate inputs over a multiyear period after the base year. We thus follow Middelhoek (1970) in the understanding of marginal input coefficients supporting not only short-range, but also medium-range planning.

Another novel aspect of our work is that we combine the conventional monetary marginal input coefficients with those pertaining to carbon dioxide (CO_2) emissions, expressed in units of tonnes of CO_2-equivalents (t CO_2-eq). Our aim here is to demonstrate the difference that marginal coefficients would make compared to average coefficients when utilized in LCA studies.

In the following sections we will first explain our methodology and then present results on a range of marginal input coefficients, which we compare with the corresponding average coefficients. In our results we highlight examples in order to confirm whether marginal coefficients match our intuitive understanding of economic trends in China. We then continue by discussing the meaning and usefulness of marginal coefficients in general, and in particular for consequential LCA in rapidly growing economies. We conclude by summarizing our work and offering the reader an outlook for future research.

Methodology

Input-output theory (Leontief 1966) defines a matrix of direct requirements, or average input coefficients,

$$\mathbf{A} = \mathbf{T}\hat{\mathbf{x}}^{-1}, \tag{1}$$

where

- $\mathbf{x} = \mathbf{T}\mathbf{1}^N + \mathbf{y}\mathbf{1}^K$ is an $N \times 1$ vector holding the gross output x_i of $i = 1, \ldots, N$ sectors[4] of an economy in monetary units, and $\hat{\mathbf{x}}$ is a diagonal matrix constructed from $\mathbf{x}$;
- $\mathbf{T}$ is an $N \times N$ matrix of intermediate demand transactions describing the input T_{ij} from sectors $i = 1, \ldots, N$ into sectors $j = 1, \ldots, N$. In our calculations, $\mathbf{T}$ includes imported commodities.
- $\mathbf{y}$ is an $N \times K$ matrix of final demand transactions describing the input y_{ik} from sectors $i = 1, \ldots, N$ into final demand categories[5] $k = 1, \ldots, K$, including imported commodities, and
- $\mathbf{1}^N$ and $\mathbf{1}^K$ are $N \times 1$ and $K \times 1$ summation operators.

There are several variants of $\mathbf{A}$, depending on whether or not $\mathbf{T}$ and $\mathbf{x}$ include imports and/or gross fixed capital expenditure (Lenzen 2001; Miller and Blair 1985). If at least imports are included in $\mathbf{T}$, $\mathbf{A}$ is also called a matrix of technical coefficients, because it reflects the production recipe of the various commodities produced in the economy. Note that changes in the elements of the $\mathbf{A}$ matrix can be caused by volume changes for the inputs into production, but also by price changes. We will return to this issue further below, but we note here that we include both volume and price effects when we use the terms "structural change" and "production recipe." In this work we examine the production recipes for a number of countries with sector classifications varying between $N = 20$ and $N = 500$.

As explained in the introduction, $\mathbf{A}^{(t)}$ represents the average production recipe for the accounting year underlying the $\mathbf{T}$ matrix. In contrast, marginal input coefficients are defined as

$$A_{ij}^{*(t)} = \frac{T_{ij}^{(t+1)} - T_{ij}^{(t)}}{x_j^{(t+1)} - x_j^{(t)}}.^{6} \tag{2}$$

These coefficients are calculated only on the basis of additional technology installed between years t and $t + 1$.

Dealing with Variability

Elements of coefficient matrices $\mathbf{A}$, however defined, are normalized according to gross output of the receiving sector, so that coefficients of small and large sectors alike range between zero and one. Due to the nature of table updating methods used by statistical agencies, the transaction values T_{ij} of sectors with small gross output x_j fluctuate much more over time than those coefficients of large sectors (Bon 1984; Jensen 1980; Jensen and West 1980; Lenzen et al. 2010; Wood 2011). The marginal coefficients $\mathbf{A}^*$ of small sectors can therefore be expected to be subject to similarly large fluctuations.

In order to avoid unwanted scatter in our $\mathbf{A}^*$–$\mathbf{A}$ plots due to small sectors with highly fluctuating transactions, we explore two approaches. First, we weight marginal input coefficients with the absolute gross output $x_j^{(t)}$ of the earlier year and plot

$$T_{ij}^{*(t)} = A_{ij}^{*(t)} x_j^{(t)} = \frac{\left(T_{ij}^{(t+1)} - T_{ij}^{(t)}\right) x_j^{(t)}}{x_j^{(t+1)} - x_j^{(t)}} \text{ versus}$$
$$T_{ij}^{(t)} = A_{ij}^{(t)} x_j^{(t)} = \frac{T_{ij}^{(t)} x_j^{(t)}}{x_j^{(t)}}. \tag{3}$$

Distinguishing Value-Added and Intermediate Inputs

Economic modeling often makes a distinction between intermediate inputs and primary inputs (such as labor and capital), which are usually recorded in their aggregated form as value added. Similarly, from an IO–LCA point of view, intermediate inputs differ from primary inputs in that they facilitate environmental impacts. It should be noted that marginal input coefficients and changes in average input coefficients do not always reflect the changes in the mix on intermediate inputs. As an example, consider the case of a process innovation where the same amount of each and every intermediate input generates additional output. In that case, the share of value added increases and all average input coefficients decrease, whereas the mix of intermediate inputs remains unchanged. In order to focus on the changes in the mix of intermediate inputs, average input ratios indicate the share of all intermediate inputs of sector *j* that comes from sector *i*. They are defined in equation (4a) and the marginal input ratios are given in equation (4b):

$$\alpha_{ij}^{(t)} = \frac{T_{ij}^{(t)}}{\sum_i T_{ij}^{(t)}} \tag{4a}$$

and

$$\alpha_{ij}^{*(t)} = \frac{T_{ij}^{(t+1)} - T_{ij}^{(t)}}{\sum_i T_{ij}^{(t+1)} - \sum_i T_{ij}^{(t)}}.^{7} \tag{4b}$$

In essence, the difference between the $\boldsymbol{\alpha}$s and the **A**s is that the $\boldsymbol{\alpha}$s refer to intermediate inputs into sector *j*, and the **A**s refer to total inputs into sector *j*.[8] Similar to equation (3), weighted and adjusted coefficients can be defined as

$$\tau_{ij}^{*(t)} * \alpha_{ij}^{*(t)} \sum_i T_{ij}^{(t)} = \frac{\left(T_{ij}^{(t+1)} - T_{ij}^{(t)}\right) \sum_i T_{ij}^{(t)}}{\sum_i T_{ij}^{(t+1)} - \sum_i T_{ij}^{(t)}} \text{ versus}$$

$$\tau_{ij}^{(t)} = \alpha_{ij}^{(t)} \sum_i T_{ij}^{(t)} = T_{ij}^{(t)}. \tag{5}$$

Dealing with Price Changes

Other immaterial changes in average coefficients can be brought about by inputs undergoing relative price changes. For example, a decrease in the average input coefficients of electronic components into other manufacturing may be due to a decrease in their price, and not due to a decrease in the overall volume of electronics used as inputs. Since IOTs are essentially monetary tables, there is in general no way to extract volume changes from them, unless commodity price data are utilized to create a physical IOT.[9] However, such recipient-specific commodity price data are generally not available in a consistent form across industries and over time.

When calculating marginal coefficients, it is important that the quantities relating to different years are comparable. Therefore, in this work we employ the IOTs expressed in constant prices to distinguish the effects of volume changes and relative commodity price changes. In addition, we use physical satellite coefficients for transforming monetary input-output matrices into units of CO_2 emissions.

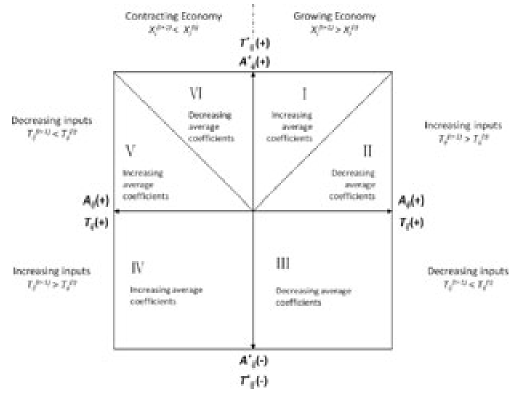

Figure 1 A panorama of economic interpretation between average input coefficients **A** and **T** (*x*-axis) and marginal input coefficients **A*** and **T*** (*y*-axis). To make the distinction between economies under growth and contraction, figure 1 is arranged as two mirror images centered at the *y*-axis.

Economic Interpretation

In this work we depict marginal and average input coefficients in scatter plots $A_{ij}^{*(t)}$ versus $A_{ij}^{(t)}$ to analyze the variations of these coefficients. Growing and contracting economies are depicted as mirror images on the right and left side of the plot, respectively. The interpretation of these figures is as follows (see figure 1).

Growing economy, increasing inputs

In a growing economy ($x_j^{(t+1)} > x_j^{(t)}$), sectors with increasing inputs T_{ij} are situated in regions I and II. Among those, sectors with increasing average input coefficients A_{ij} are situated above the diagonal (region I). In other words, if marginal and average coefficients are both positive, but the marginal coefficient is larger than the average coefficient, the average coefficient increases, that is, the average coefficient in year $t+1$ is larger than the one in year *t*. This means that input *i* is becoming more important for the production of output *j*. On the other hand, sectors with decreasing average input coefficients are situated below the diagonal (region II). This means that input *i* is becoming less important for the production of output *j*, for example, due to input-saving innovations. If, for example, gas is gradually displacing coal as fuel for new power plants, the marker for $i =$ gas and $j =$ electricity would lie in region I, and the marker for $i =$ coal and $j =$ electricity would lie in region II. In the case of pure process innovations, more output is produced with the same inputs, implying zero marginal coefficients and decreasing average coefficients, and markers will be situated on the *x* axis of figure 1.

Growing Economy, Decreasing Inputs

Sectors with decreasing inputs (and therefore also decreasing input coefficients) are situated below the *x* axis (quadrant III). If $A_{ij}^{*(t)} < 0$, an increase in gross output of commodity j ($x_j^{(t+1)} > x_j^{(t)}$) is accompanied by a decrease in the input of commodity i ($T_{ij}^{(t+1)} < T_{ij}^{(t)}$). Such a situation can occur when replacements save so many inputs that even with growing outputs, fewer inputs are required overall. An example is the electricity generation sector, where during a grid expansion, old coal-fired power plants are replaced by new gas-fired or wind power plants. In this case, $x_{j=\text{elec}}^{(t+1)} - x_{j=\text{elec}}^{(t)} > 0$, but $T_{i=\text{coal},j=\text{elec}}^{(t+1)} - T_{i=\text{coal},j=\text{elec}}^{(t)} < 0$.

Contracting Economy, Increasing Inputs

In a contracting economy ($x_j^{(t+1)} < x_j^{(t)}$), sectors with increasing inputs T_{ij} are situated in quadrant IV. Such a situation can be due to degrading technology, for example, where leaks in gas pipelines require ever more gas to be piped, but less electricity is generated.

Contracting Economy, Decreasing Inputs

Sectors with decreasing inputs T_{ij} are situated in region V and VI. Among those, sectors with increasing average input coefficients A_{ij} are situated below the diagonal (region V). In other words, if marginal and average coefficients are both positive, but the marginal coefficient is smaller than the average coefficient, the average coefficient increases. This means that input i is becoming more important for the production of output j. On the other hand, sectors with decreasing average input coefficients are situated above the diagonal (region VI). This means that input i is becoming less important for the production of output j. For example, assume a contracting economy requiring less electricity. Assume further that during this contraction, proportionally more coal-fired power plants are decommissioned than gas-fired power plants. Then the input coefficient (i.e., the importance) of coal for electricity will decrease (region VI) and that of gas for electricity will increase (region V).[10]

The diagonal lines represent the situations of constant returns to scale. In other words, for the sectors situated on the diagonal lines, increases in output require proportional increases in intermediate inputs and the production recipe remains unchanged.[11]

These economic interpretations can also be applied to quadrant plots of $T_{ij}^{*(t)}$ versus $T_{ij}^{(t)}$, α_{ij}^* versus α_{ij}, and τ_{ij}^* versus τ_{ij}^*. The diagonal lines in the quadrant plots of α_{ij}^* versus α_{ij} and τ_{ij}^* versus τ_{ij}^* indicate that no matter whether the total expenditure of intermediate inputs increases or decreases, there is no change in the expenditure shares of the intermediate inputs.

Generalizing Marginal Coefficients to Incorporate Carbon Dioxide Emissions

By the 1970s, Leontief and Ford (1970) had extended the monetary input-output formalism so it could deal with environmental externalities of economic production and other production factors expressed in nonmonetary quantities (e.g., labor measured in hours for various skill types or occupations). It was Leontief's idea to assemble such factors into separate satellite accounts that are appended to the conventional monetary input-output system below the value-added block. In the same fashion, emissions are appended in environmental satellite accounts. In what follows, we will focus on CO_2 emissions, but the analysis can be applied to handle any number of emissions and/or physical inputs simultaneously. Like intermediate inputs, emissions can be expressed as average coefficients,

$$\mathbf{q} = \mathbf{Q}\hat{\mathbf{x}}^{-1}, \tag{6}$$

where $\mathbf{Q}$ is a $1 \times N$ vector describing the CO_2 emissions Q_i of sector $i = 1, \ldots, N$.[12]

As with average input coefficients A_{ij}, marginal emission coefficients[13] can be defined as

$$q_i^{*(t)} = \frac{Q_i^{(t+1)} - Q_i^{(t)}}{x_i^{(t+1)} - x_i^{(t)}}. \tag{7}$$

As with monetary marginal input coefficients, marginal emission coefficients describe emissions in additional production between years t and $t+1$.

In order to separate the roles of $q_i^{(t)}$ and $A_{ij}^{(t)}$ in these flow matrices, we finally construct input-output flow variants χ expressed in kilograms (kg) of CO_2 per currency unit, with

$$\chi_{ij}^{(t)} = q_i^{(t)} A_{ij}^{(t)}, \tag{8a}$$

$$\chi_{ij}^{*(t)} = q_i^{*(t)} A_{ij}^{*(t)}. \tag{8b}$$

Each term $q_i A_{ij}$ describes the absolute amount of emissions in sector i "embodied" in the intermediate transaction T_{ij} to sector j, per unit of output of sector j. χ reflects the average technology with regard to the production recipe of sector j and the emission intensity of its inputs i. χ^* reflects additional technology with regard to both the production recipe of sector j as well as the emission intensiveness of its inputs i. As the original $\mathbf{T}$ and $\mathbf{A}$ matrices include imports, the assumption implicit in both cases is that imports are characterized by the domestic emissions intensity. While this is generally an untenable assumption (Lenzen et al. 2004), it is reasonable in the case of China, because emissions embodied in Chinese imports represent only around 5% of emissions from China's territory.

Data Sources

Four IOTs (1992, 1997, 2002, and 2005) expressed in 2000 constant-price renminbi (RMB) and in a 33-sector classification (table 1) are available from China Statistics Press (Qiyun Liu and Zhilong Peng 2010). Data on sectoral CO_2 emissions were taken from the Emission Database for Global Atmospheric Research (EDGAR) database (European Commission et al. 2011), Carbon Dioxide Information Analysis Center (CDIAC 2011), Energy Information Administration (EIA 2011), and the International Energy Agency (IEA 2011), and a number of national statistical agencies.

Table 1 The 33-sector classification of China

Sector Name	*Symbol in* graphs
Agriculture, forestry, and fishing	*
Coal mining and processing	+
Crude petroleum products and natural gas products	+
Ferrous ore mining	+
Nonmetal minerals mining	+
Food and beverages	o
Textiles	o
Wearing apparel	o
Wood products	o
Paper products	o
Petroleum refining and coking	o
Chemical products	o
Nonmetallic mineral products	o
Metal smelting	o
Metal products	o
Electrical and machinery	o
Transport equipment	o
Electric machinery and equipment	o
Electronic and communication equipment	o
Instruments, meters, and other measuring	o
Other manufacturing products	o
Scrap and waste	o
Electricity and steam production and supply	♦
Gas production and supply	♦
Water production and supply	♦
Construction	□
Transport and warehousing	X
Post	X
Wholesale and retail trade	◊
Hotels and restaurants	◊
Finance and insurance	◊
Real estate	◊
Other services	◊

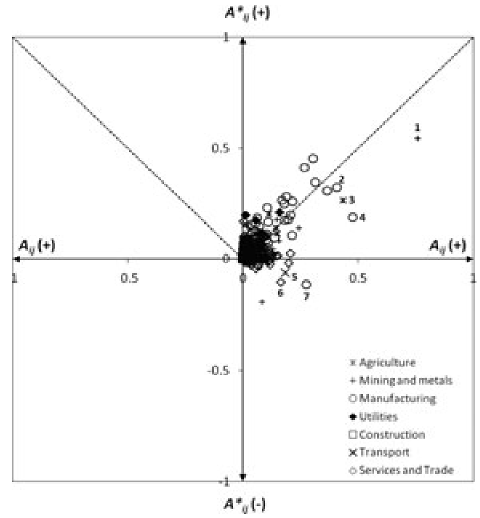

Figure 2 A comparison of average input coefficients **A** (*x*-axis) and marginal input coefficients **A*** (*y*-axis) for China's production recipe in 1992 and 2005, expressed in the 33-sector classification. Points for which $\mathbf{A} = \mathbf{A}^*$ lie on the diagonal dotted line. Each sector marker refers to the selling sector; the symbol concordance is shown in table 1.

Results

Average Versus Marginal Coefficients

Figure 2 shows a typical comparison between average 1992 coefficients (*x*-axis) and marginal 1992–2005 coefficients (*y*-axis) for the example of China. The plot is based on the 33-sector classification, and thus shows 33 × 33 marker points, with the marker symbol referring to the selling sector. We find a significant scatter of marginal coefficients around the diagram's diagonal defining $\mathbf{A} = \mathbf{A}^*$, thus clearly showing that average production recipes may differ substantially from marginal production recipes. Indeed, most of the values lie below the diagonal, indicating that, per unit of gross output, additional production has utilized, in monetary terms, less intermediate inputs than average production.

Our broad sector grouping reveals many primary (∗), mining (+) and manufactured (o) inputs that are characterized by high **A** and **A*** values, indicating that these inputs often represent a major component (mostly up to 50%) of a particular production recipe. This holds especially for transactions involving mining products, such as crude petroleum and natural gas for petroleum refining and coking (75% for the outlier marker +1 in figure 2). Some typical transactions that need fewer inputs marginally than on average are metal smelting for metal products (o2), agriculture for food and beverages (∗3), and textiles for clothing (o4). This can be understood as input-saving changes, as explained in the section "Economic Interpretation." In terms of transactions such as transport and warehousing for wholesale and retail trade (X5), real estate for finance and insurance (◊6), and textiles for other manufacturing products (o7), an increase in output was possible even with decreasing inputs.

Figure 2 does not allow distinguishing small sectors (likely undergoing large data fluctuations) from large sectors. In other words, an important input into a small sector (e.g., sugarcane into sugar refining) appears in the same region of the diagram as an important input into a large sector (e.g., nonmetal mineral mining and cement into construction). As explained in the methodology, we therefore scale the data according to equation (3). As a result, figure 3 shows the same data set as figure 2, but transformed into average and marginal transactions **T** and **T***.

We can now discern that primary (∗), mining (+), and manufactured (o) inputs are featured among the most important inputs, but some services (◊) occur. The most important transaction represents the intrasectoral transaction in the agriculture industry (∗1). Following in importance are the intrasectoral transaction in chemical products (o2) and the textiles

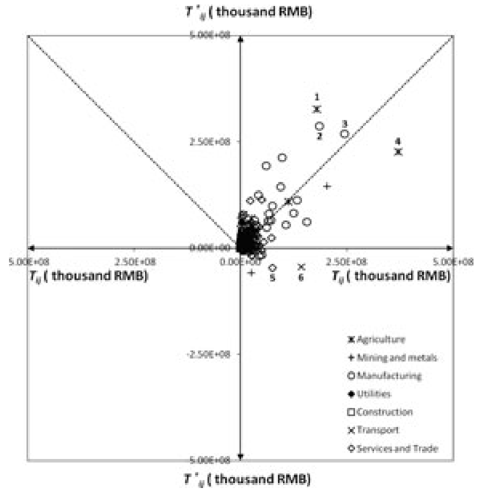

Figure 3 A comparison of scaled average input coefficients **T** (x-axis) and scaled marginal input coefficients **T*** (y-axis) for China's production recipe in 1992 and 2005, expressed in the 33-sector classification. Points for which $\mathbf{T} = \mathbf{T}^*$ lie on the diagonal dotted line. Each sector marker refers to the selling sector; the symbol concordance is shown in table 1.

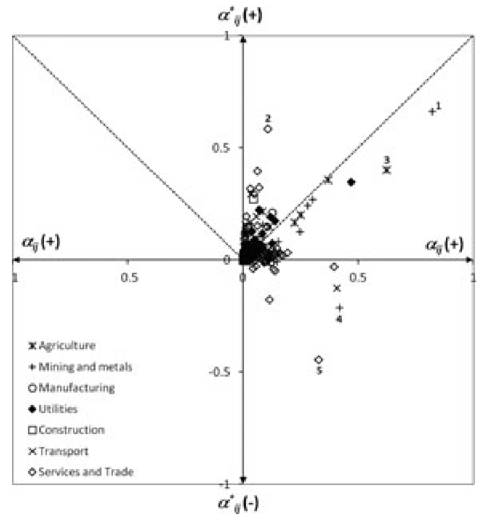

Figure 4 A comparison of average input coefficients $\boldsymbol{\alpha}$ (x-axis) and marginal input coefficients $\boldsymbol{\alpha}^*$ (y-axis) for China's production recipe in 1992 and 2005, expressed in the 33-sector classification. Points for which $\boldsymbol{\alpha} = \boldsymbol{\alpha}^*$ lie on the diagonal dotted line. Each sector marker refers to the selling sector; the symbol concordance is shown in table 1.

industry (o3), and crops for food and beverages (∗4). Once again, the finance and insurance sector registered growth, but used fewer monetary inputs in the form of real estate (◊5). This could be due to sufficient offices having been built primarily during a short boom period (which includes 1992), with little or no need for additional offices afterwards. The transaction of transport and warehousing for wholesale and retail trade shows the same characteristic (X6). Due to the scaled view in figure 3, we can conclude that these transactions are not only important relative to other inputs of these sectors, but also important in absolute terms in the Chinese economy. Apart from this, the data shown in figure 3 do not alter significantly the conclusions gleaned from figure 2. All sectors, whatever their broad grouping, may in principle undergo significant technology changes.

Value Added versus Intermediate Inputs

As described in the section "Distinguishing Value-Added and Intermediate Inputs," it is possible to define marginal coefficients that apply to intermediate inputs only. Indeed, once value added is separated out, average and marginal production recipes are now, on average, less similar to each other, which is visible in the points (figure 4), and which is also evident in the slopes of the regression lines (see table 2). The regression slope in figure 2 is 0.67 for $A_{ij}^{*(t)}$ versus $A_{ij}^{(t)}$ and 0.86 for $T_{\mathrm{ij}}^{*(t)}$ versus $T_{\mathrm{ij}}^{(t)}$ in figure 3. In figure 4 it is 0.62 for $\alpha_{ij}^{*(t)}$ versus $\alpha_{ij}^{(t)}$, and 0.75 for $\tau_{ij}^{*(t)}$ versus $\tau_{ij}^{(t)}$ in figure 5. We explain this result by relative increases (in a growing economy) in value added (e.g., in wages and salaries) being smaller than relative increases in intermediate inputs.[14] In other words, intermediate inputs are "catching up" in importance with value added.

Since the α and τ coefficients reference intermediate transactions T_{ij} to their sum $\sum_j T_{ij}$, they cannot all increase or decrease at the same time (see endnote 7). Therefore, when α versus α^* and τ versus τ^* are depicted in a diagram, markers clouds must contain markers above and below the diagonal, which is evident in figure 4. Transactions represented by marker points above the diagonal have become more important in the input mix of the production recipe, and vice versa. As a consequence of value added being excluded in the α and τ coefficients, the transactions represented by marker points located above the diagonal are the ones being displaced by the supplies of services (◊) and manufactured products (o) to sectors such as finance and insurance, material products, and transport. These transactions have grown in importance in China's economy at the expense of extractive industries.

Table 2 presents a comparison of findings of the kind shown in figures 2–5, but instead of showing diagrams for all years, we calculate the slopes b of the transactions' marker point "clouds" using linear regressions $A_{ij}^* = bA_{ij}$, and so on.

Table 2 shows that marginal coefficients were smaller than average coefficients except for 2002–2005. Figure 6 reveals a clear upward trend of slopes b, and hence of marginal coefficients over time. For the years up to 2001, we see that the marginal coefficients are smaller than the average coefficients. This implies that the average coefficients decrease over time (for growing outputs).

The counterpart of the average **A** and **T** coefficients is the value-added coefficient, which hence increases over time. However, its growth slows down (marginal coefficients come closer to the average coefficients, as reflected by the upward trend

Table 2 Slopes b and Student's t from regressions of the data in figures 2–5 for China, but for various time intervals between 1992 and 2005

Time interval	$\mathbf{A}^*$–$\mathbf{A}$		$\boldsymbol{\alpha}^*$–$\boldsymbol{\alpha}$		$\mathbf{T}^*$–$\mathbf{T}$		$\boldsymbol{\tau}^*$–$\boldsymbol{\tau}$	
	b	t	b	t	b	t	b	t
1992–2005	0.67	16.8	0.62	11.8	0.86	19.8	0.75	19.7
1992–2002	0.69	13.2	0.63	4.2	0.77	12.9	0.66	3.3
1997–2005	0.94	29.9	0.87	22.6	0.94	28.6	0.88	29.0
1992–1997	0.67	6.3	0.58	4.9	0.79	4.9	0.58	4.5
1997–2002	0.80	13.5	0.63	4.1	0.77	16.8	0.73	8.9
2002–2005	1.04	28.7	1.04	21.9	1.10	23.0	1.01	19.1
Weighted average	0.86 ± 7.6%		0.83 ± 10%		0.91 ± 5.7%		0.84 ± 6.9%	

in the slope) and even turns into a decline according to the observations for point 2003.5.

Slopes of $b < 1$ show that there are more sectors with decreasing average $\boldsymbol{\alpha}$ coefficients than increasing average $\boldsymbol{\alpha}$ and $\boldsymbol{\tau}$ coefficients, meaning that the average coefficients of many intermediate inputs (e.g., agriculture and mining; see figures 4 and 5) decrease at the cost of the coefficients of some intermediate inputs (e.g., services) increasing. The $\boldsymbol{\alpha}$ are normalized (see endnote 7), so the many sectors with decreasing $\boldsymbol{\alpha}$ coefficients must overall be sectors with smaller $\boldsymbol{\alpha}$ coefficients. The slopes have increased over time, and hence the sectors with decreasing average $\boldsymbol{\alpha}$ and $\boldsymbol{\tau}$ coefficients have become fewer, and/or the decrease of their average $\boldsymbol{\alpha}$ and $\boldsymbol{\tau}$ coefficients has slowed down. At the same time, the sectors with increasing average $\boldsymbol{\alpha}$ and $\boldsymbol{\tau}$ coefficients have become more numerous. By 2005 the initial situation had reversed, with the average coefficients of as many intermediate inputs decreasing and increasing.

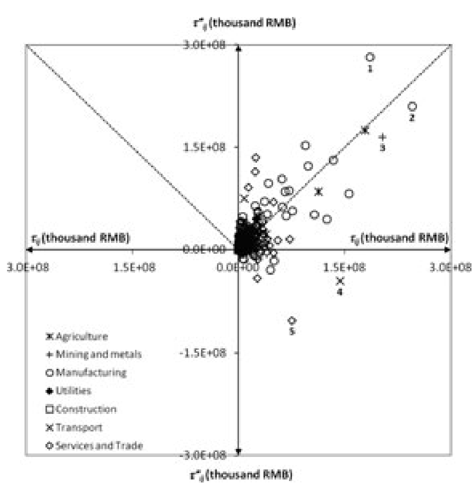

Figure 5 A comparison of average input coefficients $\boldsymbol{\tau}$ (x-axis) and marginal input coefficients $\boldsymbol{\tau}^*$ (y-axis) for China's production recipe in 1992 and 2005, expressed in the 33-sector classification. Points for which $\boldsymbol{\tau} = \boldsymbol{\tau}^*$ lie on the diagonal dotted line. Each sector marker refers to the selling sector; the symbol concordance is shown in table 1.

Marginal Change in Carbon Dioxide Emissions

Because this special issue is about "greening growing giants," we now focus on marginal changes in CO_2 emissions. Figure 7 shows a comparison of marginal versus average CO_2 coefficients for China determined according to equations (6) and (7). Markers on the diagonal line in figure 7 show that new technology in these sectors had no increasing or decreasing effect on CO_2 emission intensity. Given the logarithmic scale of the diagram, it becomes evident that marginal and average intensities differ substantially, indicating a more pronounced change in the CO_2 intensity of production compared to the monetary production recipe. All sectors, except petroleum refining and coking (o3), metal smelting (o4), real estate (◊5), scrap and waste (o9), other manufacturing products (o14), and hotels and restaurants (◊15), have registered marked decreases in CO_2 intensity, especially in the sectors of gas production and supply (♦1), ferrous ore mining (+12), and construction (□16).

The χ and χ^* introduced in equation (8) combine CO_2 intensities and monetary input coefficients (expressed in kilograms of CO_2 per RMB). In order to demonstrate a variation to the kind of results we have presented so far, figure 8 is a

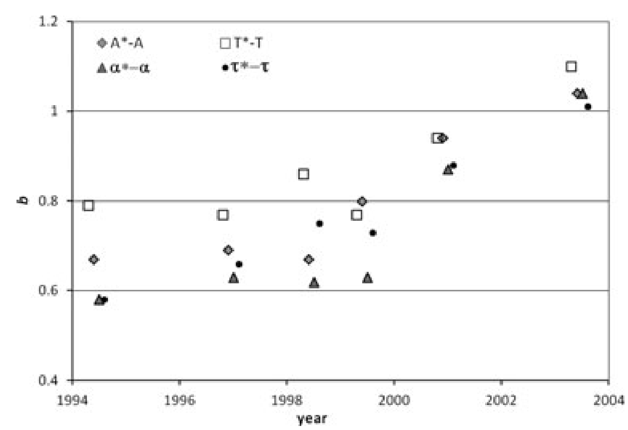

Figure 6 Slopes b from regressions of the data in figures 2–5 for China, plotted against the mean of the time intervals. For example, the **A***–**A** slope, 0.67 (see table 2, column 1), for the interval 1992–2005 was plotted at x = 1998.5.

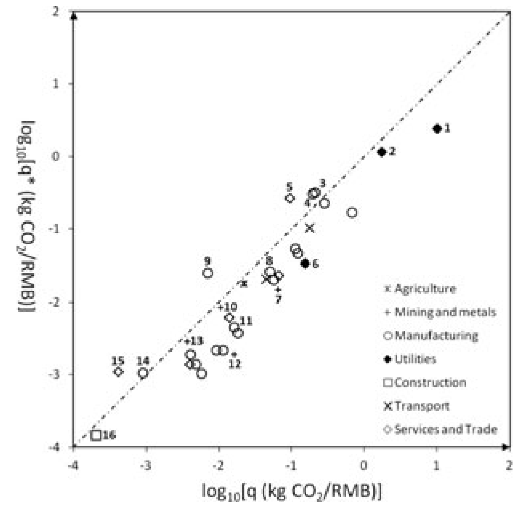

Figure 7 Comparison of average CO_2 coefficients $\mathbf{q}$ versus marginal CO_2 intensities $\mathbf{q}^*$ for China's economy 2002 and 2005, expressed in the 33-sector classification. The markers are calculated from $\log_{10}(\mathbf{q}^*)$–$\log_{10}(\mathbf{q})$.

plot showing χ and χ^* for 33 Chinese sectors, but as with the $\mathbf{q}^*$–$\mathbf{q}$ comparison, we calculate the marginal coefficients over the time interval 2002–2005. This allows us to identify the nearest marginal changes in overall CO_2 flows between 2002 and 2005,[15] and compare these to the 2002 average CO_2 flows. Note that the markers indicate the emissions embodied in the intermediate inputs that are required for the production of 1 RMB in sector j (i.e., $\sum_i \chi_{ij} = \sum_i q_i A_{ij}$). Equivalently, $\sum_i \chi^*_{ij} = \sum_i q^*_i A^*_{ij}$ gives the additional emissions embodied in the additional intermediate inputs that are required for 1 RMB of additional production in sector j.

Figure 8 shows clearly that the replacement of $\mathbf{A}^*$ for $\mathbf{A}$ and $\mathbf{q}^*$ for $\mathbf{q}$ sometimes results in an increase of physical transactions, particularly for the sectors of coal mining and processing (+7),

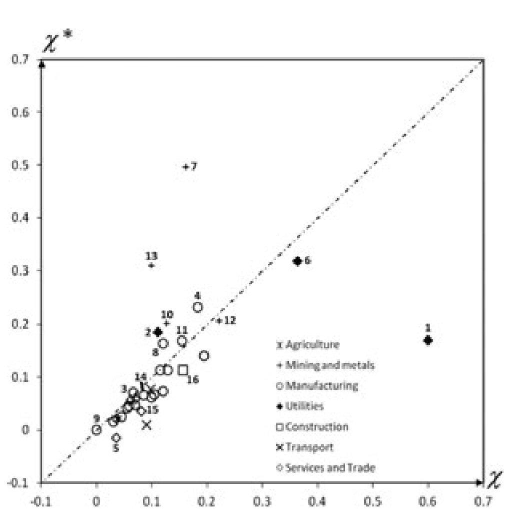

Figure 8 χ and χ^* measures calculated for the interval 2002–2005, using China's 33-sector classification and representing $\sum_i \chi_{ij}$,$\sum_i \chi^*_{ij}$ respectively.

crude petroleum products and natural gas products (+13), metal smelting (o4), nonmetal minerals mining (+10), electricity and steam production and supply (♦2), chemical products (o8), and metal products (o11). This means that, during the past decade, efforts to reduce CO_2 emissions have concentrated more on decarbonizing production processes rather than reorganizing the production recipe.

When comparing figure 7 with figure 8, it is notable that the sectors with labels mentioned above are situated below the diagonal line in figure 7. After being multiplied by marginal coefficients, they show an increase of physical transactions and are located above the diagonal line in figure 8. This means that even though technological change has brought about reductions in CO_2 emissions for these sectors, the CO_2 emissions are partly offset by structural changes in the production recipe.

These findings are important for disciplines such as input-output–assisted LCA, because they indicate that if an LCA study is to inform decision makers about the likely environmental consequences of a planned economic activity, using average intermediate input coefficients, as is common practice, will probably lead to an overestimation of impacts in an economy where technological and structural change has led to the greening of production processes. Of course, underestimation would occur in the opposite case. In addition, the relative ranking of inputs can change as well.

Conclusions

We have used the IOTs in constant price extended with CO_2 emissions for calculating marginal input coefficients in monetary as well as CO_2 terms. Marginal coefficients are increasingly mentioned in the literature, and are recommended for applications such as consequential LCA, where they are supposed to lead to more realistic results, especially in prospective analyses.

Despite their increased relevance for prospective studies, the use of marginal coefficients also comes with methodological/theoretical drawbacks. First, negative marginal coefficients cannot be understood in a causal sense, that is, that an increase in output will causally lead to a decrease in the amount of an input. Second, since marginal coefficients are derived from differences in transactions and gross output, their relative standard deviations are often much larger than those of the transactions and gross output.[16] This also means that marginal coefficients can be subject to large variability, which may in some cases preclude obtaining meaningful results. For example, we attempted a regression analysis of the relationship between average and marginal coefficients for China over 13 years, but found that the results show considerable scatter.

The use of marginal coefficients is not (yet) widespread, either in general or in consequential LCA. Our work provides a first, broad overview of the magnitude and distribution of these coefficients across recent years for which marginal coefficients could be expected to differ greatly from average coefficients. Summarizing, we find that (1) marginal coefficients can differ substantially from average coefficients, thus lending support to the need expressed in the literature for coining consequential LCA and similar prospective assessments in marginal rather than average terms. (2) In our analysis, marginal coefficients are smaller than average coefficients, indicating (for most years) a declining share of intermediate inputs in the production recipe. (3) Similarly, the upwards trend of marginal coefficients indicates that (a) the growth of value added relative to intermediate input has been slowing down, recently turning into a decline, and (b) inputs of service industries have increased at the cost of some raw material industries. (4) Marginal CO_2 emissions coefficients differ more from their average counterparts than marginal monetary coefficients, showing that for China, within-sector technological solutions to emissions abatement have played a more important role than the reorganization of supply structures. Hence, in disciplines such as consequential LCA, using marginal CO_2 coefficients appears more essential than using marginal monetary coefficients. And (5) there exists considerable scatter and variation of marginal coefficients across years, which to a certain extent precludes the identification of clear temporal and sectoral trends.

The authors are currently exploring the development of marginal analysis for environmental LCAs by employing a structural decomposition of the Leontief-type input-output impact formula. It is envisaged that structural decomposition analysis (SDA) can contribute both theoretically and empirically to the advancement of consequential LCA.

Acknowledgments

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Notes

1. For further reading on attributional and consequential LCA consult work by Curran and colleagues (2005), Ekvall (2002), Ekvall and Andrae (2006), Finnveden and colleagues (2009), Guinée and colleagues (2010), Rebitzer and colleagues (2004), Sandén and Karlström (2007), and Weidema and colleagues (1999).

2. Examples are the analysis of electricity generation (Ekvall and Weidema 2004; Lund et al. 2010; Pehnt et al. 2008), lead-free solders (Ekvall and Andrae 2006), fuel cell bus investment (Sandén and Karlström 2007), milk production (Thomassen et al. 2008), land use (Kløverpris et al. 2008), biodiesel consumption (Reinhard and Zah 2009), and corn-based ethanol production (Abiola et al. 2010).

3. For further reading on the application of marginal input coefficients consult work by Ekvall and Weidema (2004), Finnveden and Moberg (2001), Nielsen and Weidema (2001), Tillman (2000), and Zamagni et al. (2008).

4. What constitutes a "sector" can be either a more or less broad grouping of industries, or the commodities that these industries produce. All combinations exist in practice, with national statistical agencies issuing input-output tables in either industry-by-industry, commodity-by-commodity, or supply-use format (Rueda-Cantuche 2011; Rueda-Cantuche and Raa 2009; Suh et al. 2010).

5. Conventionally this is private (household) final consumption, government final consumption, gross fixed capital expenditure, changes in inventories, and exports.

6. The difference term in the denominator means that marginal coefficients are not defined for invariant outputs. However, a review of data from China, Brazil, India, and South Africa did not yield a single case where output was constant over 2 years. Note also that equation (2) can be transformed into $A_{ij}^{*(t)}(x_j^{(t+1)} - x_j^{(t)}) = A_{ij}^{(t+1)}x_j^{(t+1)} - A_{ij}^{(t)}x_j^{(t)} \Leftrightarrow A_{ij}^{(t+1)}x_j^{(t+1)} = A_{ij}^{(t)}x_j^{(t)} + (x_j^{(t+1)} - x_j^{(t)})A_{ij}^{*(t)} \Leftrightarrow A_{ij}^{(t+1)} = A_{ij}^{(t)}w_j^{(t)} + (1 - w_j^{(t)})A_{ij}^{*(t)}$, where $w_j^{(t)} = x_j^{(t)}/x_j^{(t+1)}$, meaning that the average coefficients in period $t+1$ can be expressed as a weighted average of the average coefficients in period t and the marginal coefficients.

7. The $\alpha_{ij}^{(t)}$ and $\alpha_{ij}^{*(t)}$ are normalized, that is, $\sum_i \alpha_{ij}^{(t)} = \sum_i \alpha_{ij}^{*(t)} = 1$.

8. The relationship between the $\boldsymbol{\alpha}$s and the **A**s can be written as $A_{ij}^{(t)} = \alpha_{ij}^{(t)}\phi_{ij}^{(t)}$ and $A_{ij}^{*(t)} = \alpha_{ij}^{*(t)}\phi_{ij}^{*(t)}$, where $\phi_{ij}^{(t)} = \frac{\sum_i T_{ij}^{(t)}}{x_j^{(t)}} = \frac{x_j^{(t)} - v_j^{(t)}}{x_j^{(t)}}$, and $\phi_{ij}^{*(t)} = \frac{\sum_i T_{ij}^{(t+1)} - \sum_i T_{ij}^{(t)}}{x_j^{(t+1)} - x_j^{(t)}} = \frac{x_j^{(t+1)} - v_j^{(t+1)} - x_j^{(t)} + v_j^{(t)}}{x_j^{(t+1)} - x_j^{(t)}} = 1 - \frac{v_j^{(t+1)} - v_j^{(t)}}{x_j^{(t+1)} - x_j^{(t)}}$, where $v_j^{(t)}$ gives the value added in sector j. Note that $\frac{v_j^{(t)}}{x_j^{(t)}}$ gives the average value-added coefficient. Marginal effects due to primary input (or value added) changes can hence be read from ratios $A_{ij}^{*(t)}/\alpha_{ij}^{*(t)}$.

9. For further reading on physical input-output tables consult work by Dietzenbacher (2005), Giljum and colleagues (2004), Hoekstra and Van den Bergh (2006), Hubacek and Giljum (2003), Suh (2004b), and Weisz and Duchin (2006).

10. This can be shown as follows: Assume $A_{i=\text{coal},\,j=\text{elec}}^{*(t)} = \frac{T_{i=\text{coal},\,j=\text{elec}}^{(t+1)} - T_{i=\text{coal},\,j=\text{elec}}^{(t)}}{x_{j=\text{elec}}^{(t+1)} - x_{j=\text{elec}}^{(t)}} > \frac{T_{i=\text{coal},\,j=\text{elec}}^{(t)}}{x_{j=\text{elec}}^{(t)}} = A_{i=\text{coal},\,j=\text{elec}}^{(t)}$. Multiplying by $x_{j=\text{elec}}^{(t+1)} - x_{j=\text{elec}}^{(t)} < 0$ requires a sign switch, so that $(T_{i=\text{coal},\,j=\text{elec}}^{(t+1)} - T_{i=\text{coal},\,j=\text{elec}}^{(t)})x_{j=\text{elec}}^{(t)} < T_{i=\text{coal},\,j=\text{elec}}^{(t)}(x_{j=\text{elec}}^{(t+1)} - x_{j=\text{elec}}^{(t)}) \Leftrightarrow \frac{T_{i=\text{coal},\,j=\text{elec}}^{(t+1)}}{x_{j=\text{elec}}^{(t+1)}} < \frac{T_{i=\text{coal},\,j=\text{elec}}^{(t)}}{x_{j=\text{elec}}^{(t)}} \Leftrightarrow A_{i=\text{coal},\,j=\text{elec}}^{(t+1)} < A_{i=\text{coal},\,j=\text{elec}}^{(t)}$. Similarly, $A_{i=\text{gas},\,j=\text{elec}}^{*(t)} < A_{i=\text{gas},\,j=\text{elec}}^{(t)} \Leftrightarrow A_{i=\text{gas},\,j=\text{elec}}^{(t+1)} > A_{i=\text{gas},\,j=\text{elec}}^{(t)}$.

11. This can also be seen using endnote 6: If $A_{ij}^{(t)} = A_{ij}^{*(t)}$, then $A_{ij}^{(t+1)} = A_{ij}^{(t)}w_j^{(t)} + (1 - w_j^{(t)})A_{ij}^{(t)} = A_{ij}^{(t)}$.

12. In input-output analysis, emission coefficients **q** are often used in order to quantify total emission impacts **qLy**, where $\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1}$ is the well-known Leontief inverse, with **I** being the identity matrix. In this setup, it is assumed that the emission coefficient q_i of commodity i is constant across, or independent of, the receiving industries. While this assumption is taken in virtually every input-output study, this may, strictly

speaking, not necessary be the case. For example, in Australia, emissions-intensive Queensland beef is used predominantly for exports, while less-emissions-intensive beef supplies the domestic market. Such details may only be resolved by disaggregating and/or regionalizing the input-output system (Gallego and Lenzen 2009).

13. Note that emissions coefficients (both average and marginal) are expressed in kilograms (kg) of CO_2 per currency unit.

14. Considering equations (2)–(5), it can be shown that both $\alpha_{ij}^{*(t)}/\alpha_{ij}^{(t)} < A_{ij}^{*(t)}/A_{ij}^{(t)}$ and $\tau_{ij}^{*(t)}/\tau_{ij}^{(t)} < T_{ij}^{*(t)}/T_{ij}^{(t)}$ imply $\sum_i T_{ij}^{(t)}/(\sum_i T_{ij}^{(t+1)} - \sum_i T_{ij}^{(t)}) < x_j^{(t)}/(x_j^{(t+1)} - x_j^{(t)})$, which is equivalent to $\sum_i T_{ij}^{(t+1)}/\sum_i T_{ij}^{(t)} > x_j^{(t+1)}/x_j^{(t)}$. Substituting $x_j^{(t)} = \sum_i T_{ij}^{(t)} + v_j^{(t)}$, we find $\sum_i T_{ij}^{(t+1)}/\sum_i T_{ij}^{(t)} > v_j^{(t+1)}/v_j^{(t)}$.

15. CO_2 emissions data are available from 2000. Therefore we can only analyze the marginal changes in CO_2 emissions between 2002 and 2005.

16. Error propagation shows that this is because

$$\sigma\left(A_{ij}^{*(t)}\right) = \sqrt{\left[\frac{\partial A_{ij}^{*(t)}}{\partial T_{ij}^{(t+1)}}\sigma\left(T_{ij}^{(t+1)}\right)\right]^2 + \left[\frac{\partial A_{ij}^{*(t)}}{\partial T_{ij}^{(t)}}\sigma\left(T_{ij}^{(t)}\right)\right]^2 + \left[\frac{\partial A_{ij}^{*(t)}}{\partial x_j^{(t+1)}}\sigma\left(x_j^{(t+1)}\right)\right]^2 + \left[\frac{\partial A_{ij}^{*(t)}}{\partial x_j^{(t)}}\sigma\left(x_j^{(t)}\right)\right]^2}$$

$$= A_{ij}^{*(t)}\sqrt{\left[\frac{\sigma\left(T_{ij}^{(t+1)}\right)}{T_{ij}^{(t+1)} - T_{ij}^{(t)}}\right]^2 + \left[\frac{\sigma\left(T_{ij}^{(t)}\right)}{T_{ij}^{(t+1)} - T_{ij}^{(t)}}\right]^2 + \left[\frac{\sigma\left(x_j^{(t+1)}\right)}{x_j^{(t+1)} - x_j^{(t)}}\right]^2 + \left[\frac{\sigma\left(x_j^{(t)}\right)}{x_j^{(t+1)} - x_j^{(t)}}\right]^2}.$$

For each of the four terms we observe that in general $\frac{\sigma(T_{ij}^{(t+1)})}{T_{ij}^{(t+1)} - T_{ij}^{(t)}} \gg \frac{\sigma(T_{ij}^{(t+1)})}{T_{ij}^{(t+1)}}$ and therefore $\frac{\sigma(A_{ij}^{*(t)})}{A_{ij}^{*(t)}} \gg \frac{\sigma(T_{ij}^{(t+1)})}{T_{ij}^{(t+1)}}$, and so on.

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About the Authors

Jun Lan is a PhD student and **Manfred Lenzen** is a professor of sustainability research at Integrated Sustainability Analysis (ISA) in the School of Physics at the University of Sydney, Sydney, Australia. **Erik Dietzenbacher** is a professor of economics and business at the University of Groningen, Groningen, The Netherlands. **Daniel Moran** and **Keiichiro Kanemoto** are PhD students, **Joy Murray** is a senior research fellow, and **Arne Geschke** is a research assistant, all at ISA.