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# EFFECTS OF SECTOR AGGREGATION ON CO$_2$ MULTIPLIERS IN MULTIREGIONAL INPUT–OUTPUT ANALYSES

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The past few years have seen the emergence of several global multiregional input–output (MRIO) databases. Due to the cost and complexity of developing such extensive tables, industry sectors are generally represented at a rather aggregate level. Currently, one of the most important applications of input–output analysis is environmental assessments, for which highly aggregate sectors may not be sufficient to yield accurate results. We experiment with four of the most important global MRIO systems available, analyzing the sensitivity of a set of aggregate CO$_2$ multipliers to aggregations in the MRIO tables used to calculate them. Across databases, we find (a) significant sensitivity to background system detail and (b) that sub-sectors contained within the same aggregate MRIO sector may exhibit highly different carbon multipliers. We conclude that the additional information provided by the extra sector detail may warrant the additional costs of compilation, due to the heterogeneous nature of economic sectors in terms of their environmental characteristics.

*Keywords*: MRIO databases; Aggregation; CO$_2$ multipliers

## 1. INTRODUCTION

In the pursuit of effective policies and strategies to lessen the environmental burdens of our society, a key element is the accounting scheme chosen to keep track of environmental interventions. One central accounting decision to be made is whether emissions should be tallied at the point where they occur, or at the point of final consumption of the goods or services being produced. The two schemes may be referred to as accounting from the production or the consumption perspective, respectively. Production-based accounting has the advantage of being unambiguous and rather straightforwardly measured, and it is fundamentally the same principle which is used in environmental regulations such as the US Clean Air Act and the Kyoto Protocol, where regions are made responsible for the emissions occurring within their borders.[1] Consumption-based accounting

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[1] The territorial approach, which is adopted in the Kyoto Protocol, is similar but slightly less comprehensive than the production approach, because emissions from international shipping and aviation are not allocated to any country.

(CBA) is the principle of attributing responsibilities of environmental pressures to the point of final consumption rather than to the processes where the pressures occur. For example, the $CO_2$ emissions from a steel mill are allocated to the final consumers of the products requiring the steel either directly (i.e. the final product contains steel) or indirectly (i.e. the final product required inputs of steel somewhere in its supply chain). In the terminology of CBA, consumption activities are said to *embody* a certain amount of environmental pressures, accumulated through the supply chain. The CBA principle rests on the assumption that any activity in the global economic system, and hence all emissions, occurs with the ultimate goal to deliver some product or service for final consumption.

CBA is of current interest within the realm of environmental policy-making: firstly, it facilitates the design of demand-side policies, by identifying the consumption activities that matter more or less for a given environmental issue. Secondly, it is being put forward by some as a more equitable principle for designing international climate and emissions agreements, which would also help to avoid the leakage effects experienced in the Kyoto Protocol (Peters and Hertwich, 2008; Chen and Chen, 2011; Peters et al., 2011b; Aichele and Felbermayr, 2012; Kanemoto et al., 2014).

Environmentally extended input–output analysis (EEIOA) is the prevailing method for large-scale assessments of environmental pressures embodied in consumption. Input–output analysis (IOA) is an analytical framework describing the interdependencies between the sectors of an economy, developed in the 1930s by Wassily Leontief, building on Quesnay's *Tableau économique* (Leontief, 1936). It allows the calculation of output *multipliers* or estimates of the total production output by each sector of the economy required as a result of a final demand of one unit of any sector's output. By extending the economic transactions tables of a standard input–output (IO) system with accounts of emissions or other environmental indicators, emissions multipliers rather than just economic output multipliers can be calculated by the same principles.

However, the top-down nature of IO tables implies practical limitations in terms of sector detail, which will also apply to environmental assessments based on them. To be able to track all transactions in the economy, IO table compilers aggregate small firms into broader economic sectors. The characteristics of the sectors thus represent weighted averages of the characteristics of the firms aggregated within them. For IO-based environmental assessments, such aggregations could be highly important, depending on the environmental indicator being analyzed. Sectors in IO tables are generally defined on economic rather than environmental bases, and they can represent firms with completely different environmental characteristics. Consider, for instance, a hypothetical assessment of $CO_2$ emissions embodied in brass instruments. In a typical low-detail IO system, the copper and zinc that make up the brass would be aggregated in a 'non-ferrous metals' sector, dominated by the far more $CO_2$-intensive aluminium industry, thus leading to artificially high estimates of emissions embodied in the instruments.

The recognition that detailed multiregional input–output (MRIO) tables are required for environmental assessments in an increasingly globalized and diverse economy has led to the recent development of a handful of such databases by various research groups, see Wiedmann et al. (2011) for an overview. In this paper we assess four of these, calculating $CO_2$ multipliers in each of the full databases, as well as after aggregating all four to a defined common region and sector classification system, with the aim of studying the effects of levels of sector detail on such multipliers.

The general problem of aggregation in input–output tables has been discussed extensively, see Kymn (1990) for an overview. Several authors have assessed empirically how IO coefficients and multipliers vary with different levels of aggregation.

- Based on a 1960 IO table for Philadelphia, Karaska (1968) studied how sector aggregation affected total-material coefficients for approximately 1,000 firms in the manufacturing industries, and found that aggregation even to the most detailed Standard Industrial Classification (SIC) level (four-digit, 126 industries) resulted in an average coefficient of variation (CV) of 31%.[2] Further aggregation led to an even higher variation; the average CV was 37% after aggregation to the three-digit SIC level (96 industries), and 45% for the two-digit level (19 industries). 'Assembly'-oriented sectors displayed more variation than primary sectors more dependent on a few, large inputs. A ranking of sectors according to CV values proved quite stable independent of the level of aggregation.
- Kymn (1977) studied possibilities for aggregation of the American 1963 IO table for energy forecasts, and found a significant scope for aggregation at low accuracy costs with a careful selection of sectors for aggregation.
- Katz and Burford (1981) compared the output multipliers for the 367-sector 1967 US IO table to an aggregated version with 81 sectors, and found high levels of variation among the original multipliers compared to the multipliers of their aggregate sectors.
- Bullard and Sebald (1988) applied Monte Carlo simulations to study error propagation in the 1967 US IO table, and found that when assessments were based on linear combinations of IO coefficients, errors canceled each other to the degree that overall errors were within acceptable limits – irrespective of the level of aggregation.
- Miller and Shao (1990) examined the sensitivity of output multipliers of the 1977 US MRIO table to regional as well as sector aggregation, and found scope for significant regional aggregation, while the sensitivity to sector aggregation was somewhat higher.
- Wyckoff and Roop (1994) found that carbon embodied in imports to several European countries from the USA was reduced by about 30% when calculated with a 6-sector aggregated version of the original 33-sector table.
- Lenzen et al. (2004) investigated how Denmark's $CO_2$ accounts changed in a five-region MRIO table when aggregating from an average of 118 to only 10 sectors per region, and found significant errors.
- Su et al. (2010) studied the effect of sector aggregation in calculations of $CO_2$ emissions embodied in exports for the case of China. They used the 2002 Chinese IO tables at four levels of sector aggregation, and found that a level of around 40 sectors was sufficient to capture the majority of the embodied emissions.
- Lenzen (2011) showed that disaggregation of IO data is preferable to aggregation of environmental extension data, even if based on only a few data points.
- Bouwmeester and Oosterhaven (2013) studied carbon and water footprints using the EXIOBASE MRIO database, and quantified effects of sector and region aggregation. Their findings largely agree with Su et al. (2010) in the number of sectors required; however, this varied strongly across countries.

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[2] The coefficient of variation is the same as relative standard deviation, i.e. standard deviation divided by the mean.

In this paper, we capitalize on the recent availability of a suite of MRIO databases with global coverage to study how the level of sector detail may affect multipliers used for environmental assessments. Though the aggregation issue has been studied before, it has mostly been treated theoretically, or based on experiments with hypothetical or small-scale tables. Furthermore, most of the older works in the above list have dealt with purely economic assessments, and the rest have generally been focused on total footprints rather than multipliers. Many of the studies found that sector aggregation may not be a big issue; however, there is reason to believe that this might not be the case for environmentally extended IOAs. There are two main reasons for this. Firstly, while there are technological limits to the variation in economic inputs and value-added coefficients between industries, emission intensities can easily differ by orders of magnitude from one industry to the next. Secondly, no matter the aggregation level of an input–output system, at some level firms will be grouped together, typically based on similarity of outputs and processes. However, processes that appear otherwise similar may in fact be very different if studying non-monetary factors such as labor or environmental interventions. For example, if studying lead pollution, it would be advantageous to have aviation fuel separate from automotive fuel.

We experiment with four of the largest global-coverage MRIO databases available, studying how $CO_2$ multipliers change when tables are aggregated. Compilers of these databases have chosen different levels of detail. While a highly detailed database may intuitively seem desirable, there would be clear advantages with more aggregated MRIO databases if they can be justified in terms of model accuracy. A more aggregate table can save compilers as well as analysts both time and money, and in practice, users may not always desire tables that are too detailed as the model results can be hard to interpret. It should also be noted here that the construction of a highly disaggregated IO table may be complicated by the fact that many firms have diverse product ranges that are not easily distinguished. If IO compilers allocate such firms to the sector that most closely resemble what is considered their main output, the more disaggregated system can in fact lead to a worse representation of the actual processes for such firms. However, IO systems constructed from supply and use tables (SUT) do not suffer from this problem as sectors are allowed multiple outputs.

We chose to conduct the analysis at the multiplier rather than the footprint level. This allows a better understanding of the MRIO databases' sensitivity to aggregation, since results are independent of final demand volumes. A multiplier analysis is also more useful for researchers interested in using MRIO for assessments of specific products or product groups. Readers more interested in footprints at the national level should hence bear in mind that the product multipliers are not equally important toward these totals.

In the following section, the basics of IOA are explained along with the steps taken to calculate the sets of multipliers compared. Section 3 contains the results of the analysis, while Section 4 provides a discussion of the main findings. Section 5 concludes.

## 2. METHODS AND DATA

### 2.1. Input–Output Analysis

IOA is an analytical framework using records of economic transactions between the sectors of an economy to analyze interdependencies among them. In its simplest form, an economy is described as a set of $n$ economic sectors, and the gross sales between them during the

course of a year are recorded in an $n \times n$ transactions matrix $\mathbf{Z}$, in which an element $z_{ij}$ represents sector $j$'s total purchases from sector $i$, usually in monetary terms. The transactions matrix describes how the sectors depend on each other's products in order to produce their own. In IO terminology, this inter-industrial consumption is called *intermediate* consumption, based on the assumption that all this activity takes place to enable the industrial system to ultimately deliver products to *final* consumers. Sales to final consumers are reported in an $n \times d$ final demand matrix $\mathbf{Y}$, where $d$ is the number of specific final consumption categories detailed. The columns of $\mathbf{Z}$ and $\mathbf{Y}$ together contain all sales by each sector, such that a vector $\mathbf{x}$ of gross outputs can be obtained by summing across them:

$$\mathbf{x} = \mathbf{Zi} + \mathbf{Yi} = \mathbf{Zi} + \mathbf{y}, \tag{1}$$

where $\mathbf{i}$ is a summation column vector of ones of appropriate length.

Just as $\mathbf{Y}$ consists of all sales to purchasers outside the industrial system, an IO system will also contain a value-added matrix $\mathbf{V}$ that contains each sector's payments other than purchases of the products of industry sectors. This matrix contains all non-industrial payments, such as wages, taxes, and profit. In a balanced IO system, the total payments of each sector equal its total sales, so that $\mathbf{x}$ can be obtained by summation down columns of $\mathbf{Z}$ and $\mathbf{V}$ as well:

$$\mathbf{x}' = \mathbf{i}'\mathbf{Z} + \mathbf{i}'\mathbf{V}. \tag{2}$$

In IOA, the assumption is that the observed flows represent requirements for production, so that sector $j$'s total payments, reported in column $j$ of $\mathbf{Z}$ and $\mathbf{V}$, represent its specific requirements in order to deliver its total output, recorded as the $j$th element of $\mathbf{x}$. Thus, $\mathbf{Z}$ and $\mathbf{V}$ can be normalized by the vector of total outputs to coefficient ('per-unit-output') forms:

$$\mathbf{A} = \mathbf{Z}\hat{\mathbf{x}}^{-1}, \tag{3}$$

$$\mathbf{V_c} = \mathbf{V}\hat{\mathbf{x}}^{-1} \tag{4}$$

where the circumflex ˆ represents diagonalization of a vector and subscript c denotes coefficient form. $\mathbf{A}$ is called the direct requirements matrix, because its columns represent a sector's direct input requirements from every other sector in order to produce one unit of its output.

By insertion of Equation 3, Equation 1 can now be rearranged to

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{y} = \mathbf{Ly}. \tag{5}$$

Equation 4 can similarly be expressed as a function of the final demand:

$$\mathbf{V} = \mathbf{V_c}\widehat{\mathbf{Ly}}. \tag{6}$$

The matrix $\mathbf{L}$, referred to as the Leontief inverse, gives the total (direct + indirect) output by each sector required per unit of output delivered for final consumption.

The equations above outline the most basic form of an IO system. In EEIOA, a matrix $\mathbf{F}$ containing accounts of one or more environmental extensions is appended to the tables. It is treated analytically like $\mathbf{V}$; however, it can be specified in any unit desirable and there is no particular balancing requirement. The databases assessed here, in addition to

TABLE 1.   Overview of the MRIO databases compared.

| Database name | Eora | EXIOBASE | GTAP 8 | WIOD |
|---|---|---|---|---|
| Reference year(s) | 1990–2011 | 2000 | 2004, 2007 | 1995–2011 |
| Number of regions | 187 | 44 | 129 | 41 |
| …of which were estimated | 113 | 1 | 20 | 1 |
| Number of sectors | 26–511 | 129 | 57 | 35 |
| Transaction matrix dimension | 14,760[a] | 5,676 | 7,353 | 1,435 |
| Currency | US$ | € | US$ | US$ |

[a]Note that whereas the dimension is equal to the number of regions times the number of sectors for the other databases, the matrix is larger for Eora because of the occurrence of SUTs. If only counting the number of commodities (which is greater than or equal to the number of industries) available for each region with SUTs, the system dimension of Eora is a little over 10,000, or an average of 54 sectors per region. In practice, many of the smaller countries have the minimum of 26 sectors, while larger countries may have several hundred commodities.

being environmentally extended, are *multiregional*, meaning they represent an economy consisting of several regions, each with their own set of economic sectors, all interacting with each other. The analytical framework is the same as for a single region table; however, the multiregional tables provide much better representation of internationally traded goods.

## 2.2.    The Set of MRIO Databases Analyzed

The MRIO databases studied in this analysis include the Eora, EXIOBASE, Global Trade Analysis Project (GTAP8), and World Input–Output (WIOD) databases. Out of these, Eora is the most detailed overall. It also differs from the others in that its sector detail varies among regions, from a minimum of 26 sectors up to more than 500 for the UK. Like Eora, GTAP features a high level of regional detail, specifying 129 countries and aggregate regions. The EXIOBASE and WIOD databases both have a European focus in terms of regional detail. The EXIOBASE is particularly detailed in terms of sectors, featuring a total of 129 sectors for each of its regions (Table 1). Our analysis was performed for the year 2007 for those databases available with several reference years, since this was the most recent year modeled by all these. EXIOBASE was the exception, since it was only available with 2000 as the reference year. This means that care should be taken when comparing EXIOBASE results to the other databases; however, the focus of this study is not to (directly) compare databases against each other, but rather against aggregated versions of themselves.

### 2.2.1.    *Eora*

Eora (Lenzen et al., 2012; 2013) is a time series of highly detailed MRIO tables compiled by the Centre for Integrated Sustainability Analysis at the University of Sydney. Eora contains annual tables for the years 1990–2011, and the researchers aim to keep as close to the original data of each country as possible, allowing a combination of symmetric input–output tables (SIOT) and SUT in their database, as well as allowing each region to keep its original sector classification. Eora explicitly describes 187 countries. One hundred and thirteen of these were estimated by the researchers using proxies for the initial estimate, and constrained by measured raw data from the UN (UNSD, 2011) in the reconciliation process.

### 2.2.2. EXIOBASE

The EXIOBASE MRIO database (Tukker et al., 2013) was the outcome of the EU-funded EXIOPOL project. It features 129 sectors, with special focus on environmentally relevant sectors such as agriculture, energy, and materials. The geographic focus is on the EU; all EU countries at the time of the database as well as the EU's major trading partners are explicitly described, making up a total of $27 + 16$ countries, while the rest of the world (RoW) is described as a single lump region. A drawback of EXIOBASE is that there is no time series available and the reference year is 2000. EXIOBASE is currently undergoing updates, and the new release will have 2007 as reference year, provide more sector detail and a regional disaggregation of the RoW.

### 2.2.3. *Global Trade Analysis Project*

The GTAP, based at Purdue University, has been compiling global trade databases since 1993. GTAP does not publish an MRIO directly; however, one can readily be constructed from the tables published (Peters et al., 2011a), and it has been used for several environmental assessments (Wiedmann, 2009). GTAP has a high level of regional detail and an intermediate level of sector detail, with a focus on agriculture. The present analysis was performed with version 8 of GTAP, which features 129 regions and 57 sectors (Narayanan et al., 2012).

### 2.2.4. *World Input–Output Database*

The WIOD (Dietzenbacher et al., 2013) was constructed by a European research consortium led by the University of Groningen. Like Eora, it features a continuous time series of MRIO tables, from 1995 to 2011. Its regional focus, like that of EXIOBASE, is on Europe and its main trading partners. It was mainly constructed with economic analyses in mind, but also includes some environmental extensions. It is the least detailed of the four databases assessed here.

### 2.3. The Common Classification System

A 'common classification' (CC) system, comprising a set of 41 regions and 17 sectors, was adopted for the analysis. The CC was defined so that each of the four MRIO databases could be converted to this classification through a process of straightforward aggregation, taking the principle of the greatest common factor to define regions and sectors. This scheme allowed a total of 40 individual countries which were explicitly modeled in all MRIOs. In addition, the CC system includes a bulk RoW region for completeness. The CC has a better regional detail for Europe than for other continents, reflecting the regional bias of the EXIOBASE and WIOD databases.

Our choice of using the greatest common factor aggregation principle means that each sector in the CC generally corresponds one-to-one to an identical sector in at least one of the databases. This is then the constraining database for this sector in terms of our objective of maximizing the number of sectors in the CC system without requiring any disaggregation. The existence of such direct links between the actual MRIO tables and our aggregate CC versions is an important point to make for our analysis, because it implies that each CC sector is usually an actual sector in at least one database, and as such it is relevant to discuss the effects of aggregation to this sector level. As Table 2 shows, the existence of each

TABLE 2. The sectors of the common classification system.

| # | Code | Sector name | Eora26[a] | EXIOBASE | GTAP | WIOD |
|---|------|-------------|-----------|----------|------|------|
| | | | Aggregated sectors | | | |
| 1 | AGRF | Agriculture, forestry, hunting, and fisheries | 1–2 | 1–17 | 1–14 | 1 |
| 2 | MINQ | Mining and quarrying | 3 | 18–32 | 15–18 | 2 |
| 3 | FOOD | Food products, beverages, and tobacco | 4 | 33–44 | 19–26 | 3 |
| 4 | CLTH | Textiles, leather, and wearing apparel | 5 | 45–47 | 27–29 | 4–5 |
| 5 | WOOD | Wood, paper, and publishing | 6 | 48–50 | 30–31 | 6–7 |
| 6 | PETC | Petroleum, chemical, and non-metal mineral products | 7 | 51–65 | 32–34 | 8–11 |
| 7 | METP | Metal and metal products | 8 | 66–73 | 35–37 | 12 |
| 8 | ELMA | Electrical equipment and machinery | 9 | 74–78 | 40–41 | 13–14 |
| 9 | TREQ | Transport equipment | 10 | 79–80 | 38–39 | 15 |
| 10 | MANF | Manufacturing and recycling | 11–12 | 81–83 | 42 | 16 |
| 11 | ELGW | Electricity, gas and water | 13 | 84–94 | 43–45 | 17 |
| 12 | CNST | Construction | 14 | 95 | 46 | 18 |
| 13 | TRAD | Trade | 15–18 | 96–100 | 47 | 19–22 |
| 14 | TRNS | Transport | 19 | 101–107 | 48–50 | 23–26 |
| 15 | POST | Post and telecommunications | 20 | 108 | 51 | 27 |
| 16 | BSNS | Financial intermediation and business activities | 21 | 109–116 | 52–54, 57 | 28–30 |
| 17 | PAEH | Public administration, education, health, recreational, and other services | 22–26 | 117–129 | 55–56 | 31–35 |

[a]Eora's own 26-sector CC system listed here for reference, as the full Eora database has a variable sector count depending on the region (Figure A1). The correspondence between each Eora region's sectors to the 26-sector classification is always many-to-one.

CC sector in at least one MRIO database holds true for all CC sectors except sector 17, 'Public administration, education, health, recreational and other services', where different overlapping sector definitions implied that no single sector in any database could readily be used as a CC sector to which a set of other sectors could be aggregated in the other databases. Generally, WIOD is the constraining database; although several Eora regions only include 26 sectors, those countries included in the CC system are generally more detailed in Eora. For an overview of the level of detail available in the Eora database for each of the sectors and regions defined in the CC system, the reader is referred to Figures A1 and A2 of the appendix.

## 2.4. Aggregation

For each database, the following set of matrices were used to calculate the $CO_2$ multipliers for comparison:

$\mathbf{Z}_0(mn \times mn)$, the multiregional inter-industrial transactions matrix; $\mathbf{Y}_0(mn \times md)$, the final demand matrix including direct imports; and $\mathbf{F}_0(k \times mn)$, the environmental extensions matrix.

Here, $m$ is the number of regions, $n$ is the number of sectors,[3] $d$ is the number of final demand categories, and $k$ is the number of extensions. We use $\mu$ and $\nu$ to denote the number of regions (41) and sectors (17), respectively, in the aggregate classification. Furthermore, we use the subscript 0 to refer to the full databases and 1 to refer to the aggregate versions. In the present study, $k = d = 1$, however, expanding the analysis for more stressors or more final demand categories is straightforward.

A set of binary concordance matrices was constructed in order to create aggregate (CC) versions of each MRIO database. For each database, the concordance matrix $\mathbf{C}_{01}(mn \times \mu\nu)$ was constructed from two smaller concordance matrices; one mapping region ($\mathbf{C}_{01}^{\mathbf{r}}, m \times \mu$) and another mapping sector ($\mathbf{C}_{01}^{\mathbf{s}}, n \times \nu$) according to the following algorithm:

(1)  Create a copy of the regional concordance matrix $\mathbf{C}_{01}^{\mathbf{r}}$.
(2)  Expand each element $\mathbf{C}_{01}^{\mathbf{r}}(i,j)$ to an $n \times \nu$ matrix:
      (a)  If $\mathbf{C}_{01}^{\mathbf{r}}(i,j) = 1$, insert $\mathbf{C}_{01}^{\mathbf{s}}(n \times \nu)$.
      (b)  If $\mathbf{C}_{01}^{\mathbf{r}}(i,j) = 0$, insert all-zero matrix ($n \times \nu$).

For Eora, the concordance matrix had to be slightly modified to accommodate the mixed SIOT/SUT structure. The only aggregate region in the CC is the RoW region, which in the case of Eora was constructed from 147 individual countries. Since this group included countries of both the SIOT and the SUT structure, two RoW regions were constructed for Eora.

Aggregate versions of the databases were constructed from the full versions as follows:

$$\mathbf{Z}_1 = \mathbf{C}_{01}'\mathbf{Z}_0\mathbf{C}_{01}, \tag{7}$$

$$\mathbf{Y}_1 = \mathbf{C}_{01}'\mathbf{Y}_0\mathbf{C}_{01}^{\mathbf{r}}, \tag{8}$$

$$\mathbf{F}_1 = \mathbf{F}_0\mathbf{C}_{01}. \tag{9}$$

## 2.5.  Multipliers

The comparison was performed at the multiplier level, addressing $CO_2$ emissions from all economic sectors. Three sets of $CO_2$ multipliers were calculated for each MRIO database:

$\mathbf{M}_0(1 \times mn)$, multipliers as calculated using the full tables; $\mathbf{M}_1(1 \times \mu\nu)$, multipliers as calculated using the aggregate tables; and $\mathbf{M}_{01}(1 \times \mu\nu)$, multipliers as calculated from aggregating the results of the full tables.

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[3] Note that in the special case of the Eora database, $n$ is variable. Furthermore, the matrix dimensions are larger for Eora because Eora contains supply and use tables instead of input-output tables for some regions.

For each database, the set of multipliers was calculated from the original matrices following a similar procedure as Lenzen (2001; 2011):

$$\mathbf{M}_0 = \mathbf{F}_0 \widehat{\mathbf{x}}_0^{-1} (\mathbf{I}_0 - \mathbf{Z}_0 \widehat{\mathbf{x}}_0^{-1})^{-1}, \tag{10}$$

$$\mathbf{M}_1 = \mathbf{F}_1 \widehat{\mathbf{x}}_1^{-1} (\mathbf{I}_1 - \mathbf{Z}_1 \widehat{\mathbf{x}}_1^{-1})^{-1}, \tag{11}$$

$$\mathbf{M}_{01} = (\widehat{\mathbf{Y}_1 \mathbf{i}})^{-1} \mathbf{C}'_{01} \hat{\mathbf{M}}_0 \mathbf{Y}_0 \mathbf{i}. \tag{12}$$

In the equations above, $\mathbf{I}$ is an identity matrix of appropriate dimension. Note that Equation 12 requires $k = 1$, however for larger $k$ the procedure can simply be repeated for each environmental extension separately.

To study the effect of aggregation on each MRIO database individually, the difference between 'pre-aggregated' multipliers $\mathbf{M}_1$ and 'post-aggregated' multipliers $\mathbf{M}_{01}$ was taken as a measure of aggregation error. We define $\delta^{rs}$ as the relative aggregation error in the multiplier for region $r$ and sector $s$ in the CC system:

$$\delta^{rs} = \frac{\mathbf{M}_1^{\mathbf{rs}} - \mathbf{M}_{01}^{\mathbf{rs}}}{\mathbf{M}_{01}^{\mathbf{rs}}}. \tag{13}$$

## 3.  RESULTS

CO$_2$ multipliers for the 17 CC commodities can be calculated directly from the aggregated IO systems ($\mathbf{M}_1$), or by utilizing the information available in the full tables ($\mathbf{M}_{01}$). Figure 1 shows, for six of the larger sectors in terms of gross output, how these differ in the various tables. Each plot contains one such pair for each of the 41 regions, showing $\mathbf{M}_1$ in terms of relative change $\delta^{rs}$. Those multiplier values that were calculated using the aggregate MRIOs directly generally deviate substantially from their full-table counterparts. On the whole, the more detail available in the full table compared to the CC system, the larger the effects of aggregation, as expected. The differences observed in Figure 1 are generally the smallest for WIOD, which was not aggregated much in the experiment, while the additional sector detail available in the full versions of Eora and EXIOBASE influences the CC multipliers considerably. However, the aggregation effect is not necessarily manifested (only) in the sectors that were aggregated the most. The 'Construction' sector is an interesting example, as it was not aggregated at all in either table (save for a few of the Eora regions), yet across all databases, the CO$_2$ multiplier of the Construction sector appears significantly affected by the overall aggregation process. This reflects the fact that a sector's CO$_2$ multiplier also includes emissions occurring in other sectors that supply it. On the other hand, the multiplier of the 'Electricity, gas, and water' sector in WIOD, also not aggregated in our experiment, is hardly affected at all. This is explained by the very high degree of own-sector emissions in this multiplier: for the case of Australia, the share is 97%. Conversely, this share is only 30% for the Australian Construction sector in WIOD. These values are representative across regions. For the databases other than WIOD, the spread is large because the 'Electricity, gas, and water' CC sector is disaggregated into several sectors in the respective full tables.

The aggregation effects in the Construction sector is an example of another interesting result: for all four databases, the aggregate versions give multiplier estimates for the Construction sector that are quite consistently too low compared to those found from the full tables, as evident from Figure 1. A closer inspection of the multipliers reveals why:

FIGURE 1.   $CO_2$ multipliers and their change after aggregating databases.



—— Full-model CC multipliers, M01 (kgCO2/$, left axis)        ∘  Aggregation effect, δrs (right axis)
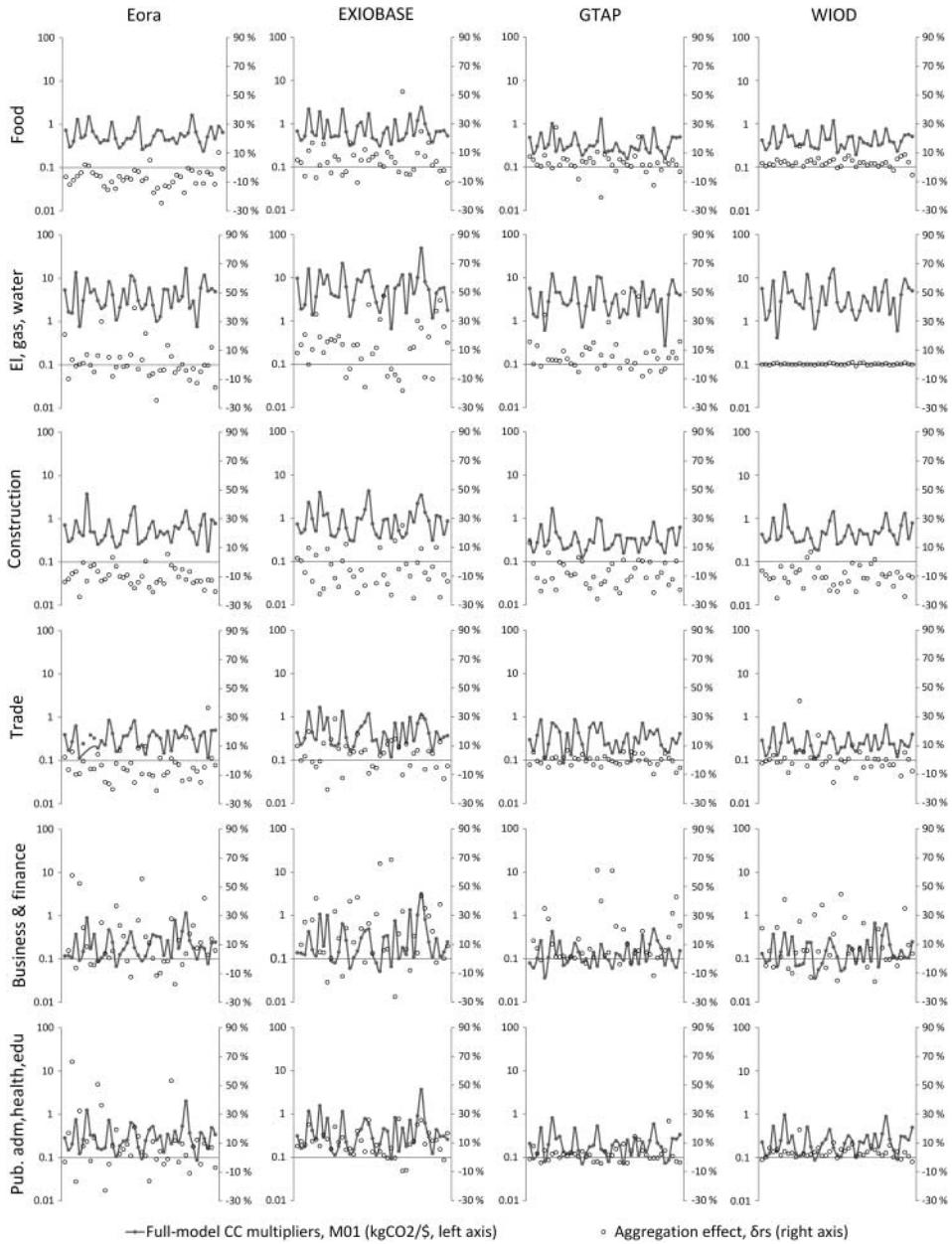
Notes: The figure shows $CO_2$ multipliers (kg/$) for six CC sectors, as calculated by the four MRIOs. Each plot shows multipliers for each region from the post-aggregation exercise (left axes), each accompanied by a marker showing the multiplier's change when using the aggregate MRIO instead (right axes).

the Construction sector requires significant inputs of $CO_2$-intensive cement. However, in the aggregation, the cement sector is aggregated with several larger but less $CO_2$-intensive sectors into the CC sector called 'Petroleum, chemical and non-metal mineral products' (PETC). Several similar instances of near consistent effects across regions for the same database were found, though sometimes in opposite directions; note for instance the Food sector multiplier, where the aggregation generally led to reductions in Eora and increases in WIOD.

Table 3 contains a quantitative overview of the trends suggested in Figure 1, showing how and to what degree $CO_2$ multipliers of various sectors tend to be over- or underestimated when tables are aggregated. The first two columns for each database show the median values of $\mathbf{M}_{01}$ and $|\delta|$ across regions (RoW multipliers excluded). For all the CC sectors and across all four aggregation experiments, the aggregation led to multipliers being overestimated for some regions and underestimated for others. Most sector/table combinations tended one way or the other, however. Interestingly, the effect of aggregating the various tables, each with different levels of detail, down to the $17 \times 41$ CC dimension was not the same. The aggregation of WIOD, with 1,435 region-sectors, a level of detail not much higher than the CC, mostly manifested itself in multipliers as overestimations. In fact, multipliers for 14 of the 17 CC sectors were mostly overestimated, 11 of them overwhelmingly so (overestimated for more than two-thirds of the CC regions). The effects were mixed for EXIOBASE (5,676 region-sectors) and GTAP (7,353 region-sectors), while for Eora ($>10,000$ region-sectors), the effects were quite the opposite: multipliers for 15 of the 17 CC sectors were mostly underestimated, 11 of which overwhelmingly. Overall, the effect of aggregation was an overestimation of $CO_2$ multipliers for 72% of the region-sectors in the WIOD experiment, compared to 71% being underestimated for Eora. Furthermore, some of the sectors for which the aggregated version of Eora most consistently underestimated the multipliers (FOOD, ELMA, TREQ, and MANF) were also among the sectors most consistently *over*-estimated in the aggregated WIOD.

The trend of underestimation of the Construction sector multiplier, suggested earlier, is confirmed in Table 3. This is an important point pertaining to product footprinting – aggregation errors need not manifest themselves only in the sectors that were actually aggregated. Hence for the Construction sector, it is the aggregation of sectors that deliver its inputs that cause the error. The Construction sector is one out of only three sectors for which the median relative change carries the same sign for all four databases.

The relative multiplier changes in Table 3 show which sector multipliers were mostly affected by the aggregation, and indicate the degree of error. Overall, sector detail mattered significantly for the calculation of aggregated multipliers in our analysis. When the multipliers are calculated with highly detailed databases such as Eora and EXIOBASE, their values change significantly from what was estimated using the aggregate tables; in the EXIOBASE case, the median change for most CC sectors is larger than 10%. Note that since these are median errors, several individual region-sectors changed significantly more, as seen in Figure 1.

The heterogeneous nature of sectors when it comes to $CO_2$ intensities is further illustrated in Figure 2, which shows all the multipliers calculated for the example of Australia. As in Figure 1, we compare the CC sector multipliers as calculated using the full ($\mathbf{M}_{01}$) and aggregate ($\mathbf{M}_1$) tables; however, Figure 2 also displays the multipliers of all the Australian sectors that are detailed in the full tables ($\mathbf{M}_0$). In other words, for each CC sector, there is one marker for each sector in the original database that was aggregated into it,

TABLE 3. $CO_2$ multipliers in full MRIO tables and the effect of aggregation.

| | Eora | | | EXIOBASE | | | GTAP | | | WIOD | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $s$ | $\tilde{M}_{01}^{:s}$ | $\widetilde{\|\delta^{:s}\|}$ (%) | +/− | $\tilde{M}_{01}^{:s}$ | $\widetilde{\|\delta^{:s}\|}$ (%) | +/− | $\tilde{M}_{01}^{:s}$ | $\widetilde{\|\delta^{:s}\|}$ (%) | +/− | $\tilde{M}_{01}^{:s}$ | $\widetilde{\|\delta^{:s}\|}$ (%) | +/− |
| AGRF | 0.35 | 6 | 12/28 | 0.52 | 18 | 31/9 | 0.39 | 13 | 18/22 | 0.43 | 3 | 36/4 |
| MINQ | 0.44 | 19 | 8/26 | 1.14 | 18 | 11/28 | 0.52 | 11 | 13/27 | 0.61 | 1 | 24/16 |
| FOOD | 0.44 | 7 | 3/37 | 0.61 | 5 | 28/12 | 0.29 | 3 | 33/7 | 0.37 | 3 | 38/2 |
| CLTH | 0.53 | 6 | 6/34 | 0.58 | 5 | 33/7 | 0.28 | 3 | 30/10 | 0.39 | 6 | 39/1 |
| WOOD | 0.44 | 6 | 15/24 | 0.73 | 7 | 29/11 | 0.38 | 6 | 17/23 | 0.42 | 4 | 33/7 |
| PETC | 0.89 | 10 | 15/25 | 1.19 | 22 | 36/4 | 0.52 | 10 | 37/3 | 0.84 | 12 | 32/8 |
| METP | 0.66 | 9 | 16/22 | 1.26 | 72 | 37/2 | 0.53 | 23 | 35/5 | 0.84 | 1 | 28/12 |
| ELMA | 0.54 | 5 | 5/35 | 0.73 | 13 | 18/22 | 0.34 | 5 | 11/29 | 0.40 | 3 | 37/3 |
| TREQ | 0.62 | 7 | 5/34 | 0.78 | 22 | 16/24 | 0.31 | 5 | 7/33 | 0.39 | 4 | 37/3 |
| MANF | 0.55 | 9 | 4/36 | 0.96 | 10 | 33/7 | 0.33 | 3 | 24/16 | 0.42 | 5 | 37/3 |
| ELGW | 3.11 | 5 | 16/24 | 5.76 | 14 | 29/11 | 2.96 | 5 | 29/11 | 2.82 | 0 | 20/20 |
| CNST | 0.51 | 11 | 3/37 | 0.85 | 10 | 12/28 | 0.30 | 11 | 8/32 | 0.43 | 11 | 3/37 |
| TRAD | 0.31 | 7 | 10/29 | 0.38 | 7 | 26/14 | 0.30 | 2 | 21/19 | 0.24 | 3 | 21/19 |
| TRNS | 1.42 | 8 | 13/27 | 1.20 | 13 | 11/29 | 1.21 | 2 | 22/18 | 0.68 | 7 | 22/18 |
| POST | 0.22 | 9 | 5/34 | 0.38 | 7 | 28/12 | 0.16 | 4 | 11/29 | 0.19 | 3 | 18/22 |
| BSNS | 0.17 | 11 | 28/12 | 0.16 | 20 | 34/6 | 0.11 | 6 | 35/5 | 0.12 | 7 | 27/13 |
| PAEH | 0.23 | 9 | 28/12 | 0.31 | 9 | 35/5 | 0.18 | 3 | 27/13 | 0.22 | 3 | 36/4 |
| Sum +/− | 192 (29%)/476 (71%) | | | 447 (66%)/231 (34%) | | | 378 (56%)/302 (44%) | | | 488 (72%)/192 (28%) | | |

Notes: For each database, the post-aggregated multipliers are shown in absolute values ($kgCO_2$/$) in the first column (median across countries, indicated by a tilde). The remaining two columns show how the multipliers change with aggregation, first as the median relative change, and second as the number of countries for which the multiplier increased/decreased following database aggregation.

FIGURE 2.    Aggregate versus original $CO_2$ multipliers (case of Australia).
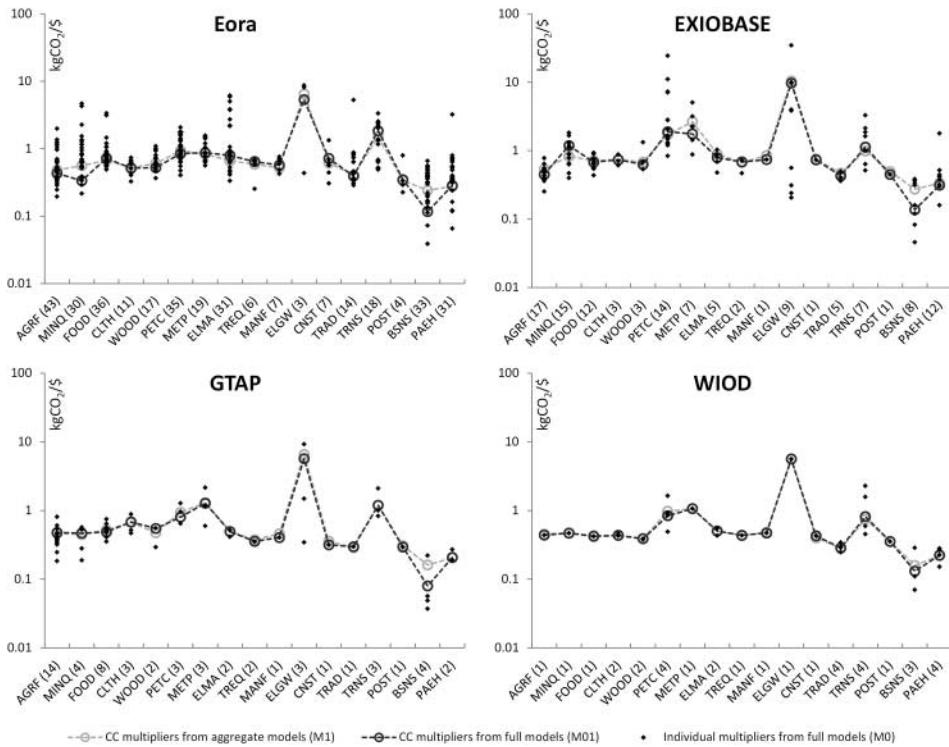


Notes: Values in parentheses indicate the number of sectors aggregated from the full to the aggregated database versions.

so that the 'EXIOBASE' panel will have a total of 129 such markers, one for each of the EXIOBASE sectors.

The aggregated multiplier values exhibit largely the same pattern whether the table was constructed from the Eora, EXIOBASE, GTAP, or WIOD database. The 'Electricity, gas, and water' sector has by far the highest $CO_2$ multiplier across all four CC versions; the multiplier of the 'Transport' sector is also relatively high; and those of the 'Metal products' and the 'Petroleum and chemicals' sectors stand out as notable spikes except in the Eora-based CC table, although they are the third and fourth highest multipliers also in this version.

By comparing the circular markers, we see how each aggregate sector's multiplier is affected by the overall level of table detail. Since the darker circles were calculated from the full versions, they may be considered 'true' multipliers, whereas the light circles representing multipliers of the aggregated tables deviate because of information loss. The more the light circles deviate from the dark ones, the more the additional information available in the full table matters for this sector. Again, in general, the more detail available in the full table, the larger the observed deviation. The $CO_2$ multipliers of the Australian 'Financial intermediation, business activities' (BSNS) sector suffer particularly from the loss of detail, and the aggregation effect is consistently an overestimation. In the same manner as for the consistent underestimation of the Construction multiplier investigated earlier, a closer

inspection of the tables can shed light on the cause of this aggregation error. Whereas the error in the Construction sector's multiplier was caused solely by aggregation of its supplying sectors, the aggregation error for the BSNS sector also comes about from aggregation of this sector itself. Generally, this type of aggregation error arises because the 'true' aggregated multiplier $M_{01}$ is ultimately a final-demand-weighted average of the multipliers of its full-table subsectors, whereas the aggregation of the full IO table into the CC version implicitly entails a weighting based on gross outputs, because the size of the individual sectors will determine the direct input requirements structure of the aggregated sector. An investigation of the Australian BSNS sector as modeled in WIOD serves to illustrate: The BSNS sector is represented as three different sectors in the full WIOD database: 'Financial Intermediation', 'Real Estate Activities', and 'Renting of Machinery and Equipment (RME) and Other Business Activities'. While the three are of comparable size in terms of gross sales, in terms of sales to final demand, the RES sector is the largest by far. At the same time, the RME sector's $CO_2$ multiplier is significantly higher than those of the other two.

The multipliers of the 'Mining and quarrying' sector for Eora and EXIOBASE also change significantly when the full systems are used for the calculation rather than the aggregate IO systems. In this case, however, the direction of the error is not the same, the aggregation leading to an overestimation in the Eora case and an underestimation in the EXIOBASE case.

The individual dot markers, showing the original multipliers in the full MRIOs, illustrate the true heterogeneity of the individual sectors (in terms of carbon footprint intensities) that form part of the aggregates. Across all databases and sectors, the internal variability in these sets of aggregated sectors is significant. For the highly detailed Eora and EXIOBASE databases, multipliers falling under the same aggregate sector routinely span an order of magnitude. This means that for a number of environmentally important sectors, using the aggregate table results in a substantial loss of information. For a tabular overview of the spread of original multipliers allocated to the same CC sector, please refer to Table A1 of the appendix.

## 4.   DISCUSSION

The aggregation experiments performed in this study resulted in rather large effects in terms of $CO_2$ multipliers. In general, the more detailed the original database, the larger the multiplier error when tables were aggregated to the CC system. No particular pattern of how these errors manifested themselves could be identified, although the multipliers of some sectors for some databases were quite consistently (i.e. across regions) too high or too low when the table was aggregated prior to the multiplier calculation. Otherwise, the effect of aggregation on a particular sector's multiplier generally varied significantly across countries, as well as from one table to the next. Only for the Construction sector, which interestingly was not aggregated at all except in some of the more detailed Eora countries, did all the tables show a coherent and significant trend, roughly a 10% underestimation when using the aggregated database versions. Another consistent (but weaker) trend was that the multipliers for the financial and administrative sectors tended to be too high when databases were aggregated. A somewhat surprising finding was a clear tendency for Eora CC multipliers to be reduced when the aggregated version was used, whereas WIOD-derived multipliers showed an equally clear tendency in the opposite direction. No explicit

explanation for this was found; however, it may be assumed that one reason lies within the two databases' highly different representation of the RoW region defined in our CC system, which is modeled as only one region in WIOD but as almost 150 individual countries in Eora.

The results of our assessment show that for product carbon footprint accounting, the additional sector detail found in the Eora and EXIOBASE databases adds information that may warrant the additional compilation efforts required, to avoid critical aggregation of sectors with highly different emission structures. Although our comparison has not directly been one of database against database, our results do provide some suggestions in this respect. The findings displayed in Figures 1 and 2 show that the $CO_2$ multipliers as calculated using the less detailed WIOD or GTAP databases could be significantly different if they had been compiled with more sector detail. If we assume that all four databases are true representations of the global economy, only with different sector and region classifications, the CC multipliers calculated using the full version of the most detailed database would be the most correct representation, and the difference between these and the same multipliers calculated from one of the less detailed databases would represent the gain in multiplier accuracy from compiling more detailed tables.[4]

Figure 2 showcases the true heterogeneity among the individual subsectors contained within each CC sector. The multipliers of the subsectors included within the same CC sector in many cases spanned an order of magnitude; this was found to be true not only in the carbon-intensive ELGW sector, but across the economic spectrum from primary and extractive sectors to administrative and service sectors. This suggests that if a less detailed table is to be used for carbon footprint accounting, the sector classification defined for this study is not ideal, because similarity in terms of economic input structures does not imply similarity in terms of emissions profiles.

We limited our study to $CO_2$ and found considerable aggregation effects on product multipliers. There is reason to believe that such effects would be even more pronounced for many other environmental extensions. While the $CO_2$ emissions profile of several sectors is linked at least to some degree to their economic structure through energy use, other environmental interventions such as Pb emissions or water use can be completely unrelated to other common measures of sector similarity, and the intensities may vary even more between sectors than $CO_2$ emissions intensities do. These factors also speak in favor of higher sector detail in MRIO tables used for environmental assessments.

The implications of our findings are different for different applications of MRIO analysis, and it should here be stressed again that the present analysis has been of multipliers' sensitivity to aggregation, and the results cannot be directly transferred to the case of carbon footprints because these are a product of demand levels as well as multipliers. Nevertheless, for carbon footprinting of individual sectors or products, the results of our analysis can be taken to say that the level of detail could influence results significantly, because of the large differences among the multipliers of specific commodities that are frequently aggregated. However, the adverse effects of this high variability will be dampened in analyses of the total carbon footprint of households or nations, which is determined not from multipliers alone,

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[4] Note that this would also require that the environmental extensions are true and equal across all the MRIO models, an assumption that is perhaps more dubious (Peters et al., 2012). For recent work on this, see Owen et al. (2014).

but as the product of multipliers and consumption volumes. For these kinds of analyses, a higher level of detail will have some, but probably more limited, influence.

## 5.   CONCLUSION

For compilers of input–output databases as well as those who want to use them for assessments of various factors embodied in consumption and trade, a recurring question is what level of detail is required for a sufficient degree of accuracy. In this paper, we have approached this question by assessing the sensitivity of $CO_2$ multipliers to sector detail. Though one of the main challenges for database compilers is now largely overcome, thanks to astounding advances in computational power, the compilation of highly detailed IO tables is still a costly and time-consuming process, and a trade-off will always have to be made, since there is virtually no limit as to the number of firms that could theoretically be included. Although several studies in the past found that a rather limited level of detail was sufficient to achieve acceptable economic output multipliers, the more recent trend of appending various social and environmental extensions to IO tables has led to renewed scrutiny of the effects of aggregation.

Our findings suggest that when conducting carbon footprint assessments using MRIO analysis, a high level of detail can significantly improve the accuracy of the results, because carbon multipliers, one of their determining factors, are sensitive to table detail. In terms of environmental intensities, such as $CO_2$ emissions or water use, it is clear that industrial processes differ tremendously, whereas in terms of pure economic structure, the variability is generally less. Although a lower level of detail may give acceptable results if firms were grouped into sectors according to their similarity in terms of the environmental stressor under study, the limiting factor these days is not so much computational power for the analysis itself, but rather the time and money spent on compiling large MRIO databases. Compiling databases specifically with, e.g. carbon or water footprinting in mind would be a possible venue; however combined efforts to build versatile and highly detailed databases appear to the authors as a more fruitful way forward.

A note should be made here that the net benefits in accuracy from increased detail suggested above will depend on the detail and accuracy with which additional sectors are added; this has not been quantitatively analyzed here. MRIO data have traditionally been published as face value numbers; uncertainties, though significant, have usually not been well understood. To improve on this situation, the researchers behind Eora have attempted to estimate uncertainties to accompany all values in their database. Such information might improve the credibility of MRIO-based analyses and promote their further use.

The aim of this analysis has been to capitalize on the current situation—historically quite unique—where a suite of MRIO databases with global coverage is available to researchers, to conduct a realistic real-data study on the effects of aggregation in input–output systems. Although we have not aimed to explicitly quantify the aggregation effects attributable to aggregations of sectors versus regions, the focus of the study has been on the overall sensitivity of sector (or commodity) carbon multipliers. Though we conclude that $CO_2$ multipliers are generally sensitive to table aggregation, we suggest future work should attempt to describe more specifically the relationship between table detail and multiplier accuracy to answer the question of what level of detail is needed to give an acceptable degree of accuracy for various types of analyses.

## SUPPLEMENTAL DATA

Supplemental material for this article is available via the supplemental tab on the article's online page at http://dx.doi.org/10.1080/09535314.2014.934325

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