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# *Uncertainties in Constructing Environmental Multiregional Input-Output Models*

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***Abstract***

With increasing interest in the modeling of global trade, international supply chains, and multi-scale environmental impacts of global production chains, the method of multiregional input-output (MRIO) modeling is enjoying substantial recent research interest. Models ranging from simple two-region models to expansive world models with more than 100 countries have been constructed. However, relatively little attention has been given to the uncertainties inherent in the method and data typically used for constructing these models. This paper examines three of the greatest uncertainties in the method through a series of models built using input-output data from the United States and several of its largest trading partners (Canada, China, Mexico, Japan, Korea, Germany, and the UK). The three major uncertainties, relating to aggregation and concordance to a common sectoral scheme, treatment of the rest-of-world (ROW) region, and monetary exchange rate issues for factor embodiments, are all shown to be major problems for MRIO models. In fact, while MRIO proponents often claim the method limits uncertainty compared to single-region models, it is likely that these inherent uncertainties often end up raising total uncertainty beyond the levels of a detailed (ie, >200 sector) single-region model, though the relative lack of understanding of underlying uncertainty in standard IO models prevents a strong comparison. Nonetheless, MRIO models offer border-specific emissions inventories and supply chain delineations, which are essential to many analyses, and thus, practitioners must understand, quantify, and to the extent possible minimize MRIO uncertainty in practice. Practical suggestions are offered for quantifying aggregation, ROW, and exchange rate uncertainties.

**Keywords**: multiregional input-output, uncertainty, aggregation, exchange rate.

## 1. Introduction

Recent years have seen an explosion of interest in the field of input-output analysis for environmental purposes, as data have become more available and reliable and researchers worldwide have looked for methods for life cycle assessment, corporate environmental management, and carbon footprinting(Tukker & Jansen, 2006). Within this growth has been a particular interest in analyzing global trade patterns and the effects of globalization on life cycle impacts of goods and services. Globalization has connected production and consumption systems around the world in ways completely new to human history; it is now commonplace for complex consumer products to contain parts or materials from several countries and dozens of locales. A wealth of recent literature from both the economics and LCA fields has sought to understand the energy and environmental implications of this growth in trade(Ahmed & Wyckoff, 2003; Lenzen et al., 2004; Muradian et al., 2002; Nijdam et al., 2005; Peters & Hertwich, 2006b; Weber & Matthews, 2007a,b).

These analyses have often used a combination of traditional single-region input-output analysis (IOA), coupled single region models, and full multiregional input-output (MRIO) models. The use of MRIO, previously a method used mostly in regional input-output studies, has become popular for global analysis only recently (see (Wiedmann et al., 2007) for a detailed review of recent international MRIO models). Several new models being discussed at this conference, including the UK-MRIO project, the Global Resouce Accounting Model (GRAM), MRIO models built from the GTAP database (Peters, 2007), and the EXIOPOL project. Each has been developed in just the past few years. Clearly a large need exists in the community or the type of results MRIO models can produce.

The main draw of environmental MRIO models has been, and continues to be, their ability to distinguish between different production patterns, energy usages, and emissions factors in different locations of global production chains. Many previous MRIO studies have assumed implicitly that overall model uncertainty will be reduced by including region-specific production and emissions patterns; it is a widely accepted premise in the community that the “imports assumption” (taking the name used in

(Lenzen, 2001) is one of the major weaknesses of IOA(Lenzen et al., 2004; Tukker & Jansen, 2006). Yet regrettably, relatively little literature has examined the tradeoffs inherent in the choice of single-region vs. multiregional models, with a few notable exceptions(Lenzen et al., 2004; Peters, 2007; Peters & Hertwich, 2008b).

The uncertainties in environmentally-extended IOA have been described in some detail by previous authors, and this paper does not attempt to duplicate this work(Hawkins et al., 2007; Lenzen, 2001). Nor do I wish to duplicate previous discussions of uncertainty in MRIO(Lenzen et al., 2004; Peters & Hertwich, 2008b). Rather I will attempt to illustrate, quantitatively where possible, a few additional error types associated with environmental MRIO analysis compared to traditional single-region IOA. For several reasons, such as limiting analysis to developed countries or starting with prebalanced and aggregated input-output tables (IOTs), previous assessments of MRIO uncertainty may have overlooked potentially large sources of error. Error types and magnitudes will of course by situation dependent, conditional on the underlying data being used to construct the MRIO model. In some cases, though, I will argue that single region models, combined with corrections for production and emissions differences in different countries, could be more effective that full MRIO models.

I hope to show this through an example of constructing a MRIO model based on the United States and several of its largest trading partners, previously discussed elsewhere(Weber & Matthews, 2007a,b). In general the construction of the model follows the methods used to create the GTAP database (Dimaranan, 2006), and constructive criticism about the use of this method will be inserted where appropriate. I start with a brief recap of the structure of MRIO models, followed by an examination of the data sources used. The next section details several of the uncertainties in combining the individual models to a MRIO model, followed by a discussion of different potential uses for single vs. multiregional models. I finish by discussing some simpler alternatives to MRIO for certain analysis types and a discussion of the implications for the future of MRIO analysis.

# 2. Basic Methods of Multiregional Input-Output Modeling

## 2.1 Full Multiregional Model

Several authors have detailed the basics of MRIO models(Dimaranan, 2006; Lenzen et al., 2004; Miller & Blair, 1985; Peters, 2007; Peters & Hertwich, 2008b; Weber & Matthews, 2007b), and thus only a brief review is presented here. As originally formalized by Leontief in his groundbreaking work in the 1950's (Leontief), the total output of an economy, **x**, can be expressed as the sum of intermediate consumption, **Ax**, and final consumption, **y**:

$$x = Ax + y \tag{1}$$

where **A** is the economy's direct requirements matrix. When solved for total output, this equation yields:

$$x = (I - A)^{-1} y \tag{2}$$

The equation can be generalized for an open economy, where only output related to country 1 is considered, to (UN DESA, 1999):

$$x = (A_{11} + \sum_{j \neq 1} A_{j1})x + y_{11} + \sum_{j \neq 1} y_{1j} - \sum_{j \neq 1} y_{j1} \tag{3}$$

where $\mathbf{A_{11}}$ is the domestic portion of the direct requirements matrix (domestic interindustry demand on domestic goods), $\mathbf{A^m} = \sum_{j \neq 1} A_{j1}$ is the import matrix (domestic use of imports to make domestic output), and $y_{11}$, $y^m = \sum_{j \neq 1} y_{j1}$, and $y^{ex} = \sum_{j \neq 1} y_{1j}$ represent domestic final demand on domestic production, imports from all countries to final demand in country 1, and exports from country 1 to final demand in all other countries, respectively(Peters, 2007).

This equation can be expressed in matrix form for the m-region multiregional case, where each of m countries imports from every other country, to both interindustry demand as well as final demand:

$$\begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{pmatrix} = \begin{pmatrix} A_{11} & A_{12} & \cdots & A_{1m} \\ A_{21} & A_{22} & \cdots & A_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ A_{m1} & A_{m2} & \cdots & A_{mm} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{pmatrix} + \begin{pmatrix} y_{11} + \sum_{j \neq 1} y_{1j} \\ y_{21} + \sum_{j \neq 2} y_{2j} \\ \vdots \\ y_{m1} + \sum_{j \neq m} y_{mj} \end{pmatrix} \tag{4}$$

which shows the relation between total production in each country, $x_j$, and final demand in each country, both from domestic production ($y_{mm}$) and from imports ($\sum_{j \neq m} y_{mj}$). Each country $y_{j1}$ represents imports from country j to final demand in country 1 and $y_{1j}$ represents country 1's exports to final demand in all other countries(Peters, 2007).

Equation (4) can be solved for total output, **x**, and further for total emissions or factor embodiment (such as energy) with the use of a region and sector-specific factor embodiment vector, **F** = **f***diag(**x**), where **f** represents the total emissions or factor use by each sector in each region:

$$f = F(I - A)^{-1} y \tag{5}$$

where **f**, **F**, **A**, and **y** each represent compound vectors or matrices with dimension *mn* x 1 or *mn* x *mn*, where *n* is the number of sectors in each region.

## 2.2 Common Model Simplifications

### *2.2.1 Assumptions for studies of embodied emissions in trade*

MRIO models are used for different purposes, and common simplifications are made to simplify model construction when appropriate(Nijdam et al., 2005; Peters & Hertwich, 2006b; Weber & Matthews, 2007b). As Peters and Hertwich have explained, for the now fairly common studies of embodied emissions in trade (EET), two accounting frameworks, each of which produces the same total world emissions, can be used. Following their framework(Peters, 2007), we label these the 'embodied emissions in trade' (EET) framework and the 'embodied emissions in consumption' (EEC) framework. The difference between the two is how each allocates what the authors term "through-trade", or what Lenzen et al. termed "multi-directional trade"(Lenzen et al., 2004).

The EEC framework is essentially the full model shown above in equation 4. Its advantage is that it properly delineates the global supply chain of each final demand through infinite levels of trade between all modeled economies. For example, if the Chinese economy requires a semiconductor device from the U.S. to create a computer it will then export to the U.S., the emissions associated with making the semiconductor made in the U.S. will be allocated to the U.S. and modeled with U.S. technology. In this way, the EEC framework is the full “consumption perspective”(Munksgaard & Pedersen, 2001), and the framework is fully correct in that it makes no approximations of trade structure. However, the framework has two disadvantages. The first is that it is usually (see below) necessary to aggregate the IO tables to a common sectoral classifcation in order to avoid rectangular off-diagonal elements. With several different countries, the necessary level of aggregation may be rather high since each country has a different set of original sectors in their table. The second disadvantage is that bilateral trade data cannot be used directly since an assumed split must be made between imports used by interindustry and imports which go directly to final demand(Peters, 2007). While the import penetration assumption can be used to accomplish this, when performed at an aggregated level this assumption can yield significant errors.

The second accounting framework that can be used, EET, solves both these problems with the EEC framework, though has an alternative disadvantage of misallocating through-trade from a consumption perspective. For EET all embodied emissions in exports (EEE) are allocated to the exporting country, regardless of whether they may return to the exporting country in its imports, as in the semiconductor-computer example above. Accounting is thus similar to the economic concept of border tax adjustments, where excise taxes on goods are added at the border to imports and rebated at the border for exports(Ismer & Neuhoff, 2004). The model is simplified to:

$$\begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{pmatrix} = \begin{pmatrix} A_{11} & 0 & \cdots & 0 \\ 0 & A_{22} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & A_{mm} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{pmatrix} + \begin{pmatrix} y_{11} + \sum_{j \neq 1} y_{1j} \\ y_{21} + \sum_{j \neq 2} y_{2j} \\ \vdots \\ y_{m1} + \sum_{j \neq m} y_{mj} \end{pmatrix} \qquad \textbf{(6)}$$

Where $y_{ij}$ now represents total bilateral trade from country i to country j regardless of how the imports are used (ie, in final demand or in interindustry demand). This model structure allows for each country's IO table to be used in its native sectoral structure since no off-diagonal matrices are used, clearly advantageous for reducing aggregation error(Weber & Matthews, 2007a; Peters & Hertwich, 2008a). Further, the final demands in the model are fully consistent with bilateral trade data.

*2.2.2 Unidirectional Trade Assumption*

While both the EET and EEC models have advantages, some analysts have found it useful to strike a middle ground of unidirectional trade to infinite order into a single country of interest, often called "unidirectional trade models"(Peters & Hertwich, 2008b). The advantage of such models is to allow modelling of arbitrary final demands, ie by households, while still limiting data and model balancing requirements (more on this below). Basically, these models assume that direct trade (aka first-level trade) dominates overall trade so that off-diagonal elements of the compound A matrix are assumed zero. The effect is to redirect the remainder the supply chain to the current trading partner if 2 or more borders are crossed in a good's production. Several authors have cited Lenzen et al.'s influential study for justification for this assumption; they found that the error in cutting off such feedback loops to be around 1-2%(Lenzen et al., 2004). The unidirectional model is shown in equation 7.

$$\begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{pmatrix} = \begin{pmatrix} A_{11} & 0 & \cdots & 0 \\ A_{21} & A_2 & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ A_{m1} & 0 & \cdots & A_m \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{pmatrix} + \begin{pmatrix} y_{11} + \sum_{j \neq 1} y_{1j} \\ y_{21} \\ \vdots \\ y_{m1} \end{pmatrix} \quad \textbf{(7)}$$

# 3. Example MRIO Model Construction

## 3.1 Single Region Input-Output and Environmental Data

Armed with this background, I begin with a discussion of the data sources that will be used in the illustrative examples below. Detailed sources for all data discussed herein are available in previous publications(Weber & Matthews, 2007a,b). The desired model is a full multidirectional trade MRIO model for the year 2002, amended with CO2 emissions data for each country, derived from national energy and environmental statistics. In many countries, $CO_2$ data was not available at the same level of detail as in the input-output table, and for these countries emissions were allocated by output (similar to (Lenzen et al., 2004; Peters & Hertwich, 2006b).

Input-output data details are shown in Table 1. It is clear that despite best intentions, IOTs are available for several different years and in varying levels of detail. A striking difference lies between the most detailed IOT of the U.S., at 491 sectors, and the least detailed of the E.U. members at 59 sectors (the UK table was taken from the OECD input-output database (Yamano & Ahmad, 2007) and has only 48 sectors). Similarly, different classification schemes are used for all of the tables (discussed below), and only for a limited number of the countries are detailed make and use tables or import matrices ( $A_{im} = \sum_{j=1}^{n} A_{ji}$ ) available. Finally, tables are available at different pricing schemes, with the U.S. and its two largest trading partners (China and Canada, as well as Japan) available at producer prices and the remainder of countries available at basic prices.

In addition to the input-output data, to create a balanced world model, one needs data on the overall size of each of the economies to be modelled, as well as the world economy as a whole for balancing the rest-of-world (ROW) sector. Here the data is taken from the International Monetary Fund’s World Economic Outlook database for 2005(IMF, 2006), and can be seen in Table 2. A few things can be noted about this data; first, despite having several of the world’s largest economies in 2002 included, the ROW sector is still very large, roughly 60% of the world economy. Second, large differences exist between estimates of the size of several economies using market exchange rates (MER) and purchasing power parity (PPP) rates to convert the country’s currency into the international dollar, which is the standard unit for measuring trade(IMF, 2006; UN DESA, 1999, ; Yamano & Ahmad, 2007). Implications are discussed in the following section.

# 4. Uncertainties in Single Region and Multiregional Models

## 4.1 Single Region Models: Standard Uncertainties of Environmental IOA

While the uncertainties in standard single-region environmental input-output models have perhaps not received the attention they warrant due to difficulties in estimating several of them, there has been some past work in the field(Bullard & Sebald, 1988; Hawkins et al., 2007; Hendrickson et al., 2006; Jackson & West, 1989; Lenzen, 2001). Much of the previous work in the field might be better labelled sensitivity analysis rather than uncertainty analysis because oftentimes underlying error and correlation structures have been assumed with no prior information on the uncertainty in underlying input-output data(Morgan & Henrion, 1990). One particular study, Lenzen's work comparing conventional life cycle assessment to environmental input-output analysis, has been influential(Lenzen, 2001), and the base uncertainties analyzed therein are shown in Table 3, reprinted with permission from (Hawkins et al., 2007).

One of the reasons uncertainty analysis has likely been somewhat lacking in the environmental IOA field is the relative lack of information on the size or structure of many of the types of uncertainty listen in Table 3. Because input-output models are created by central statistical agencies within governments, many of the calculations which go into transforming underlying survey data into balanced IOTs are not public(Peters & Hertwich, 2008b). Thus, it becomes difficult to analyze such uncertainties as source data uncertainty (for the IOT), transaction estimations, proportionality assumptions (for all sectors which do not produce a single homogenous output), and harmonization uncertainties. Some of the other uncertainties in Table 3 can be approximated using different methods, such aggregation uncertainty using successive aggregations (Lenzen, 2001; Williams, 2006), though this method is limited in that one can only disaggregate to the point of the maximum number of sectors for the IOT.

Due to this lack of information on error structure, oftentimes errors are simply assumed and monte carlo (MC) simulations are used to estimate resulting posterior distributions on energy or emissions multipliers. One of the common results from literature has been that errors in multipliers tend to be significantly smaller than errors in input data due to stochastic cancelling(Bullard & Sebald, 1988; Hawkins et al., 2007; Lenzen et al., 2004). For example, for an aggregate sector with some high-impact commodities and some low-impact commodities, different supply chain purchases of both the high- and low-impact commodities will cancel and lead to the average sectoral direct multiplier.

In contrast to these data uncertainties which will tend to cancel due to IO model structure, some of the inherent uncertainties in environmental IOA will bias total multipliers in a specific direction. Aggregation of the input final demand sector (the commodity which is being modelled) is probably a more severe problem than aggregation of other sectors in its supply chain, for instance, since the direct multiplier for the sector itself will be biased either high or low. Similarly, temporal lag of IOTs will usually produce total environmental multipliers that are too high, since in most countries energy efficiency tends to improve with time (Williams, 2006).

The problem of imports, commonly called the “imports assumption”(Lenzen, 2001), see Table 3) or the “import penetration assumption” (Weber & Matthews, 2007b), is another uncertainty which is unlikely to cancel out given that in general a country’s trading partners will produce their exports with different production patterns and more importantly, different energy and environmental intensities. The error will only stochastically cancel if trading parters with higher environmental intensities are cancelled by other trading partners (of the same commodity) with lower environmental intensities. As previously stated, the underlying interest in MRIO models is to attempt to reduce this uncertainty by explicitly modelling the production location of a country’s imports. Other problems with MRIO models, such as the need to aggregate IOTs to similar sectoral structures, may be of the cancelling form (to a point), and thus the move from a single-region to a MRIO model would theoretically change a non-canceling error to a cancelling one. However, as we shall see, other additional uncertainties in MRIO complicate this potential uncertainty reduction.

### 4.2 Additional Uncertainties Associated with Multiregional models

Several uncertainties associated with environmental MRIO are either nonexistent or latent in similar single region models. Peters and Hertwich (Peters & Hertwich, 2008b) and Lenzen (Lenzen et al., 2004) have reviewed in broad terms the many empirical issues with MRIO model construction, including grouping of like regions to reduce data collection, estimation of interindustry trade flows from bilateral trade data, inflation/deflation of data from different years, different sectoral schemes, different valuation of IOTs, aggregation of IOTs, and exchange rates. Each of these are potentially important for overall model uncertainty. I will not repeat these valuable discussions, but instead will look in detail at three of these issues as the sample data from Tables 1 and 2 are combined into a full multidirectional MRIO model.

### *4.2.1 Rest-of-World (ROW) Approximation/Region Grouping*

To approximate the world economy in any given year not only must the economies of interest be included, but also a grouping of all other countries. These other countries are commonly referred to as the rest-of-world (ROW). A full multidirectional model including the ROW must include both trade flows coming from the ROW into the economies of interest as well as exports from the modelled countries to the ROW. As can be seen from table 2, despite including several large U.S. trading partners, the ROW region block still accounts for \$32 x $10^{12}$ in 2002, or approximately 60% of the world economy measured at market exchange rates.

There are two main options for the ROW countries, including them all in a single ROW block of the model(Lenzen et al., 2004; Weber & Matthews, 2007) or grouping them together with the modelled countries based on some measure of similarity(Peters & Hertwich, 2006b; Weber & Matthews, 2007b). Each has advantages and disadvantages—a single ROW block is easier to deal with empirically with trade share approximations (Lenzen et al., 2004), but a grouping may be more appropriate since it allows different ROW countries to be treated differently according to some metric. Of course, there is no standard metric for deciding which modelled country a certain ROW country is most similar to; past suggestions for studies of $CO_2$ emissions in MRIO have included GDP/person, $CO_2$ emissions/GDP, $CO_2$ emissions/total primary energy, etc. (Nijdam et al., 2005; Peters & Hertwich, 2006b; Weber & Matthews, 2007b). However, such groupings would be very difficult to deal with for multidirectional models; the trade share approximation of off-diagonal elements make this method more applicable to unidirectional models(Peters & Hertwich, 2008b).

Thus, I will assume a block ROW will be used, and two choices immediately come up: the relative economic size of the block and its structure. Past studies have chosen relatively large and broad economies to represent the ROW (the U.S. is a common choice), and the choice is usually governed simply by convenience (Ahmed & Wyckoff, 2003; Lenzen et al., 2004; Weber & Matthews, 2007a). The choice has some fairly major implications, though, given the relative size of the ROW in models with a small portion of world GDP represented. For example, assume the U.S. is chosen as a convenient ROW country. To scale the model correctly, the U.S.'s economy must be increased to the approximate size of the ROW, or by a factor of around 3 (From $10.5 trillion to $32.5 trillion in 2002). This scaling must also be done in some form to convert models of different years to model year 2002. One method to accomplish this is scaling GDP to match the GDP from a central database as in Table 2. This assumes the structure of GDP remains constant between the year of the IOT and the year of the MRIO model (Dimaranan, 2006; Peters, 2007).

To balance the model correctly, the blocks $A_{1m}$ to $A_{mm}$ of equation 4 must represent trade flows, properly valued in basic prices from either cif or fob(Lenzen et al., 2004), from the modelled countries to the ROW block. Since the ROW block is simply an approximation based on the U.S. IOT, splitting the modelled countries' exports to the ROW into exports for industry and exports for final demand is entirely arbitrary. It must be assumed, and basing the split on the U.S. is problematic given that the U.S. may constitute large portions of the world sectoral output for some commodities (ie, semiconductors) but not others (ie coffee). How this split is done matters considerably for the ROW production function, and is probably why some authors in the past have avoided it altogether by using only unidirectional trade flows from the ROW (Lenzen et al., 2004). A related problem is that for the model to balance the consumption pattern (structure of GDP) for the ROW sector must be included and in general this structure is unknowable except for a few homogenous sectors. Perhaps the best method is to assume a scaled $A_m = \sum A_{im}$ or more likely $Z_m = \sum Z_{im} = A_m * diag(x_m)$, and subtract off the approximated imports to industry:

$A_{mm} = A_m - \sum_{i \neq m} A_{im}$, followed by a balancing using the RAS method(Lenzen et al., 2004).

Perhaps even more important than the ROW economic balancing is the assumed environmental intensities of the ROW. Lenzen et al. compare Australian-assumed ROW intensities to average world intensities from disparate sources; however, these average world intensities can only be found for a few key industries. In truth, world averages might not even be appropriate, since the remaining ROW trade going into any given country might be dominated by one or two nations which are not well-represented by the world average. As shown below, environmental intensities can vary considerably between countries, and the range for all world countries is rather large. Weber and Matthews (Weber & Matthews, 2007a) perform a sensitivity analysis by assuming the ROW is represented by the most $CO_2$-intensive and least $CO_2$-intensive countries in the data below and find considerable variation due to this uncertainty, on the order of 20% of total embodied emissions of $CO_2$.

*4.2.2 Aggregation issues*

Depending on the purpose of the study, there may or may not be a need to aggregate IOTs to a common sectoral format. In general when the EEC or multidirectional trade model types are used it will be necessary, though for studies of embodied emissions in trade the most detailed sectoral structure should be used to avoid aggregation error, which can be severe for studies using a very aggregated classifcation system(Ahmed & Wyckoff, 2003; Lenzen et al., 2004; Weber & Matthews, 2007b).

The reason for aggregation should be clear—in general IOTs from different countries use different systems to define economic sectors and have very different levels of detail (see Table 1). Most countries, including the European Union (directly) and Japan, Korea, China, and Mexico (somewhat more loosely), use some system based on the International Standard Industrial Classification (ISIC) system, now in its 3$^{rd}$ revision with a 4$^{th}$ revision in draft form. However, different systems exist, and North America (Canada, the U.S., and Mexico) have now converted to the North American Industrial Classification System (NAICS), and other countries define their sectoral schemes purely based on shares of different commodity groups in their domestic economy(Lenzen et al., 2004). For these reason, most large international databases, such as GTAP (Dimaranan, 2006) and the OECD input-output database (Yamano & Ahmad, 2007) use a single structure that all IOTs are reclassified to in the preparation of the database or model. The number of sectors in any MRIO model will thus be dependent on both how well the more detailed sectors from different IOTs match and the limits of the least detailed table (here the UK at 48 sectors).

It is constructive to ask how important aggregation error is for environmental IOA, and in which sectors it is likely to be important. Lenzen and colleagues specifically analyzed aggregation to a 10 sector structure and found significant errors, particularly due to aggregating electricity together with gas and water production(Lenzen et al., 2004). However, 10 items is more aggregated than most of the MRIO models in use or development today, many of which are based on either GTAP or the OECD input-output database. Using these sectoral schemes, Tables 4 and 5 show summary statistics of aggregating total $CO_2$ multipliers (in mt $CO_2$/\$M 2002) from the recently completed 426 sector 2002 version of the EIO-LCA model, (Green Design Institute, 2007) into these common formats. Of course, as mentioned above, this only approximates aggregation error to the extent that the sector groupings in the 426 sector Benchmark U.S. IOTs are better distinguished than the GTAP or OECD sectors. For some sectors, such as the well-defined agricultural sectors in GTAP or some service sectors in OECD, the U.S. detailed IOTs offer no more detail than the aggregate schemes. Nonetheless, for some sectors comparing between the U.S. CO2 multipliers and the aggregate schemes leads insight into some potential problems with their use.

For example, both schemes have a number of aggregate sectors with large coefficients of variation (the ratio of standard deviation to mean) of 1 or above. Of particular importance are pulp, paper, and publishing; chemicals; other nonmetal minerals; and post and telecommunications. They are problematic for different reasons. For pulp, paper, and publishing, the problem comes in combining 6 low-impact publishers with 7 medium impact paper products manufacturers and 3 high-impact pulp and paper mills sectors. Aggregate chemicals sectors have a similar large range of impacts, whereas the large potential aggregation errors in nonmetal minerals and post/telecommunications are due to one relatively large impact sector amidst many low or medium impact sectors (cement manufacture for nonmetal minerals and couriers and messengers for post/telecommunications).

It is at least conceivable to maintain the sectoral structure of each of the countries' IOTs without aggregation by using rectangular off-diagonal matrices ($A_{ij}$ where $i \neq j$ in equation 4) and this has been demonstrated by past authors (Lenzen et al., 2004; Weber & Matthews, 2007b). However, this method has several problems, not least that the difficulty of balancing rectangular hybrid structures increases quickly with an increasing number of countries in the model. The other issues are more complex: consider that aggregation error occurs for two reasons in MRIO models, aggregation of trade flows between different regions (off-diagonal $A_{ij}$'s) and aggregation of flows within a domestic economy (diagonal $A_{ii}$'s). I will call the latter interior aggregation and the former exterior aggregation for illustrative purposes. Rectangular off-diagonal matrices in theory solve interior aggregation error, since no aggregation is necessary in domestic matrices, and minimize exterior aggregation error. This is only true, though, if trade flows are allocated to the correct sector in each economy, and this is not possible with rectangular trade matrices.

For instance, take a binational model submatrix between the U.S. (country *i*, 491 sectors) and the U.K. (country *j*, 48 sectors). The rectangular trade matrices would thus have dimensions $A_{ij}$ = 491x48 and $A_{ji}$ = 48x491. Consider the submatrix of the $A_{ij}$ matrix where 5 sectors from the U.S. table flow into 1 sector of the UK table. The trade and trade share data from the UK are unlikely to be at a sectoral detail greater than the IOT, so data from the UK will yield a 1x48 vector of UK use of US exports of a commodity in the UK sectoral system. The US data, after correcting for valuation and splitting exports into exports for industry and final demand, will yield a 5x1 vector of total exports from the U.S. to UK industries. Somehow these two vectors (5x1 and 1x48) must be converted into 5x48 submatrix representing every industry in the UK's use of each of the 5 exporting sectors from the U.S, although there is no remaining data to constrain this underconstrained problem.

Similarly, using trade shares and the U.S. import matrix (Lenzen et al., 2004; Peters & Hertwich, 2008b), $A_{ji}$ can be approximated at the same sectoral level as the US

IOTs (491x491) and then must be aggregated to the appropriate rectangular size (48x491) using a concordance between U.S. and UK sectors. While this $A_{ji}$ submatrix will generally be more accurate itself than the $A_{ij}$ submatrix, since it was derived at a more detailed level then aggregated, it is still problematic in that detail is lost in moving from the US imports table, where 491 distinct imported commodities are modelled, to the UK-US flow matrix where only 48 distinct commodities are modelled. For instance, whereas the US imports table may allow imports of semiconductors or hard drives to flow to computer manufacturers, the UK-US flow matrix will only allow imports of the aggregate “office and computer machinery” sector, which includes intermediate and final products in both categories and thus has a total $CO_2$ multiplier indicative of this average.

*4.2.3 Currency Conversion Issues*

Conversion of currencies has long been recognized as problematic in MRIO construction(Ahmed & Wyckoff, 2003; Peters, 2007; Weber & Matthews, 2007a). Since each country’s IOT is derived in local currency and trade data is generally in terms of international dollars, it becomes necessary to convert all currencies to a common unit to produce a full multidirectional MRIO model with a ROW block. Some past authors have suggested the use of hybrid currency units to get around this issue (Lenzen et al., 2004) but this is only possible because the ROW block is modelled unidirectionally. In any case, several reasons make currency conversion a worry for MRIO modellers, even if hybrid units are used. First, it is impossible to compare multipliers between countries without converting multipliers to a common currency, e.g kg $CO_2$/$(Ahmed & Wyckoff, 2003). Second, if hybrid units are used modellers must use final demand inputs in hybrid currencies as well, which may be difficult for users unaccustomed to foreign currency units. Third, even with hybrid units there is an implicit conversion of trade data, usually by the local government’s customs officials, from international valuation to local valuation, and thus it behooves MRIO users to understand this conversion whether or not it is present in their model.

The basic issue surrounding currency conversion has been a discussion of whether it is more appropriate to use market exchange rates (MERs), the published exchange rate between a country’s currency and $USD, or purchasing power parity rates (PPPs), a measure of the price level of consumption within a country, to convert gross output between countries(Ahmed & Wyckoff, 2003; Weber & Matthews, 2007a). The issue parallels a discussion in the climate change literature over which of these conversion rates is more appropriate to compare and project future incomes(IPCC, 2007; Nordhaus, 2007). The problem is that due to development levels, price levels in developing countries tend to be much different than in developed ones, leading to a somewhat large difference between the MER and PPP. Table 2 below shows GDPs of the countries discussed here converted to 2002 $USD by both rates (data taken from the Penn World Table 6.1 (Heston et al., 2006), and the ratios of the rates (MER/PPP), which range from 0.9 in Japan to 4.7 in China. Most of the developed countries in the model have ratios around 1, implying similar price levels as the U.S. However, the developing countries have larger ratios, from 1.4 in Mexico to 1.6 in Korea and a whopping 4.7 in China due to a pegged and purposefully undervalued currency.

The upshot of this difference is that depending on whether the MER or PPP rate is used to convert Yuan to $USD, the modeller gets total multipliers in $CO_2$/$ around 400% different. Of course, this is for the economy-wide PPP rate, which includes all goods and services. Newer data from the recently performed International Comparison Programme of the World Bank (World Bank, 2008) show that sector price levels in 2005 varied from a low of 0.69 for health expenditures and a high of 8.79 for machinery and equipment expenditures. If available, sector-specific price level data will certainly act to reduce the large uncertainty in developed-developing country interactions in MRIO models.

The question of which of the currency conversion rates is “correct” almost certainly depends on the two countries and the specific commodity group in question. In general, the desired conversion rate should be the ratio of gross output prices, since the desired effect is to convert the physical unit price of gross output in the foreign country (e.g. yuan/kg) to the physical unit price of gross output in the country of reference ($/kg). Consider modelling the production of 1 MWh of electricity in the U.S. and in China. The proper price to input into either model is the gross output producer’s price of electricity, or $x_i/g_i$, where x is gross output of sector i is g is physical unit output of sector i. This price can be compared between the countries of interest for a number of sectors where output is fairly homogenous, and this is done in Figure 1 below for coal, electricity, iron and steel, and cement.

Figure 1 shows the ratio of the Chinese gross output price in 2002 to the U.S. gross output price in the same physical unit, which cancels to an implied conversion rate between the 2002 RMB and the 2002 $USD (both in producer's prices). The price ratio of electricity is rather close to the market exchange rate of 8.1 RMB/$US while the ratio for coal is considerably higher at almost 15 RMB/$US and the ratio for steel and cement are between the MER and PPP at around 5.6 for iron and steel and 4.2 for cement. Interestingly, there seems to be relatively little intuition in which commodities tend closer to the MER or PPP rates, as intuition might lead one to believe that products which are very open to trade might be valued at closer to the internationally-traded MER whereas products produced mostly for domestic consumption should trend more toward the PPP. Counterintuitively, these four examples show that it is the less traded products (electricity and coal) which are close to or above the MER and the more open product, iron and steel, is in between the MER and PPP.

Perhaps the best approach to dealing with the PPP/MER issue, other than simplistic sensitivity analysis (Weber & Matthews, 2007b), would be to use hybrid currencies within the compound A matrix (Lenzen et al., 2004), along with sector-specific exchange rates to convert the environmental direct multipliers into a common currency for comparison and for converting final demand inputs. As expressed above, this would only be possible if a unidirectional ROW sector is assumed, as balancing the model to the world economy requires a common currency, at least in assumption, to define ROW output. The sector-specific rates should be defined by physical unit comparisons where possible (as above) and price level comparisons such as PPP components where available.

## 5. Comparing Usefulness of Detailed Single Region Models to MRIO

Given all these potential drawbacks of MRIO, what can be done for practitioners who would like to model global supply chains? The answer will of course depend on the underlying data, the goals of the study, and the relative importance of different uncertainty types to the study's goals.

One crucial decision point will be the quality and detail of the single region IOT and environmental data available. For the current exploratory example, a single region global model could be approximated at the 491 sector level using the U.S. EIO-LCA model and the imports similarity assumption. Tables 4 and 5 show that aggregation would be an issue in developing a MRIO model at the level of detail of the least detailed trading partner. Of course, the model's detail could be improved considerably by only using a few of the more detailed IOTs in the MRIO model, such as only using the 1997 producer priced models of the U.S, Canada, and China. Around 100 common sectors could be defined between the U.S. and these two largest trading partners, and this would help minimize the aggregation error in the analysis. Of course, the MER/PPP problem would still be present with the Chinese currency and the ROW would be rather large with only 3 regions. Further, these issues are in addition to the other, harder to quantify additional uncertainties of MRIO, such as classification uncertainties, valuation of trade data and IOTs, etc(Peters & Hertwich, 2007).

This scenario stands in contrast to a potential MRIO model for a smaller nation which has most of its trade associated with bordering countries, typical of some EU countries. If the classification system of the IOT in the country of interest is already fairly aggregated, such as in the E.U. with its 59 sector models, not much information is lost in aggregation and most trading partner data is already available in a similar classification and valuation system. Although ROW uncertainty will still be high, there would certainly be a gain in information by moving from a single region 59 sector model with the import similarity assumption to a simplified MRIO model with several linked 59 sector IOTs.

The use of preconstructed databases such as OECD or GTAP surely saves time and effort, though in both these databases aggregation is more extreme than in most countries' base IOTs, and this can cause serious errors as seen above. Additionally, past work has suggested that some of the alterations done in the GTAP database to prepare the model for its computable equilibrium simulation capabilities introduce further uncertainties (Peters, 2007). Both the aggregation and CGE uncertainties will hopefully be minimized in the production of the EXIOPOL model, which holds great promise for the future of MRIO modeling.

Where detailed IOTs and environmental data are available, such as here, some alternatives may be available for global supply chain modelling. One option is to keep the detailed economic structure of the IOT while splitting domestic and imported production through a simplified 2 region MRIO model of the country of interest and the ROW (see (Weber & Matthews, 2007a) for an example). For example, for the U.S. a 982 sector model could be derived simply by splitting the U.S. IOT into domestic production and a ROW assumed similar to the U.S. This method adds information to single region IOA by allowing the detailed breakdown of impacts happening within the country of interest and outside the country of interest to make arbitrary final demands. By scaling the ROW sector to world-average (Lenzen et al., 2004) or trade-weighted trading partner average environmental intensities, a passable approximation of the real world may be achieved, though this method will of course assume economic structure is equivalent to the country of interest even if environmental intensities are scaled.

A more advanced single-region approximation could fully account for multidirectional trade, differences in environmental intensities, and structural differences in economic efficiency through the use of structural path analysis (SPA) (Peters & Hertwich, 2006a). Deriving a structural path using detailed single-region IOA and then correcting portions of the tree structure with process data or another single-region IOA result from a trading partner would get around many of the issues above, including aggregation, exchange rate uncertainty, reclassification and deflation, and ROW uncertainty.  (that is, if the specific country of origin of each portion of the supply chain is known) This method would be akin to a hybrid life cycle assessment, where input-output analysis and process analysis are brought together to solve many of each other's respective weaknesses(Bullard et al., 1978; Suh et al., 2004). While this may sound ideal, it must of course be remembered that this method would take a somewhat large amount of time for any single commodity, and is probably only appropriate for uses of MRIO for a single or a few specific commodities. While the creation of an MRIO model also takes a significant amount of practitioner time, it is usable for any arbitrary final demand once it is constructed.

## 6. Summary and Conclusions

It is clear that several large uncertainties exist in the creation and use of environmental MRIO models, though it is also clear that their use is increasing due to the increasing desire to model international trade and differences in production practices across countries. Different modellers choose MRIO for different reasons, and for some uses (such as approximating multidirectional trade for a large number of commodities in countries with less detailed IOTs) the advantages of MRIO models probably outweigh the additional uncertainties in their use.

However, as argued here, it is important to remember that MRIO models are no panacea for modelling the impacts of global trade. The necessary aggregation and simplification, along with exchange rate uncertainty, rest-of-world assumptions, and several other unquantifiable uncertainties make MRIO a minefield for practitioners desiring fairly accurate numbers. There is no doubt that the many uses of MRIO models in the past years have led to further understanding of many issues, most notably the importance of global trade for environmental issues (Wiedmann et al., 2007). However, given the uncertainties, detailed single region models with simplified trade modelling should also be considered, especially if the analysis only requires a few commodities to be modelled and a hybrid analysis using SPA is possible.

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# Tables:

**Table 1**

| | IOT Year | Sectors | Make/Use | Import Matrix | Pricing | Imports, $B | Exports, $B |
|---|---|---|---|---|---|---|---|
| Canada | 1997 | 117 | no | no | Producer | 232 (17%) | 160 (23%) |
| China | 1997 | 122 | no | no | Producer | 154 (11%) | 22 (3%) |
| Germany | 2000 | 59 | yes | yes | Basic | 72 (5%) | 26 (4%) |
| Japan | 2000 | 104 | no | no | Producer | 141 (10%) | 51 (5%) |
| Korea | 2000 | 168 | no | no | Basic | 42 (3%) | 23 (3%) |
| Mexico | 1989 | 92 | no | no | Basic | 153 (11%) | 98 (14%) |
| United Kingdom | 2000 | 48 | no | yes | Basic | 45 (3%) | 33 (5%) |
| Rest of World | 1997 | 491 | yes | yes | Producer | 512 (38%) | 281 (40%) |
| United States | 1997 | 491 | yes | yes | Producer | - | - |

Unaltered IO Table data with year of data, number of sectors, availability of make/use detail and import matrix, pricing system, and total imports to U.S. and exports from U.S. associated with the country or group

**Table 2**

| | GDP, own | GDP, $B US | own/$US | PPP, own/$US | MER/PPP |
|---|---|---|---|---|---|
| Canada | 1158 | 738 | 1.57 | 1.19 | 1.32 |
| China | 10517 | 1271 | 8.28 | 1.76 | 4.72 |
| Germany | 2107 | 1990 | 1.06 | 0.93 | 1.14 |
| Japan | 498045 | 3979 | 125 | 144 | 0.87 |
| Korea | 684264 | 548 | 1249 | 737 | 1.69 |
| Mexico | 6262 | 648 | 10 | 7 | 1.43 |
| United Kingdom | 1044 | 1568 | 0.67 | 0.65 | 1.02 |

| | | | | | |
|---|---|---|---|---|---|
| Rest of World | - | 32420 | - | - | - |
| United States | 10487 | 10487 | 1 | 1 | 1 |

Data on Gross Domestic Product for model countries and rest of world block of countries in country's national currency ("own"), $2002, market exchange rate (MER) of national currency, purchasing power parity (PPP) rate, and ratio of MER/PPP.

**Table 3**

| **Source of Error** | **Description** |
|---|---|
| Source data uncertainty | Uncertainty arising from the estimation of elements of the IO accounts based regression of standard errors of survey data. |
| Estimation of transactions | Certain industries included in an IO account are not surveyed directly and therefore transactions must be calculated based on total expenditures. Make table production and use table supply chains are adjusted to increase correlation between primary industries and commodities. Finally entries in the make and use tables are adjusted to balance the total output values. |
| Allocation uncertainty | When an industry produces multiple products a portion of revenue and expenditures must be allocated to each. Environmental impacts and material use must also be allocated across products. Often it is unclear how these allocations should be performed. |
| Proportionality assumption uncertainty | Uncertainty due to the assumption that unit flows of commodities represented by monetary transactions are the same for all industries. Proportionality uncertainty also arises from the assumption that effects respond linearly to changes in the production level. |
| Gate-to-grave truncation error | Most IO LCA models only consider requirements and impacts due to the production of goods and services while not providing guidance related to use, maintenance, decommissioning, demolition, disposal or recycling. |
| Changes in technology or production mix over time | New technologies, new processes, or changes in production level leading to gain or loss of economies of scale would each change the structure of the direct and indirect requirements matrices and lead to different model results. Generally the time elapsed between the US Economic Census and the BEA release of input-output tables is 5 years. |
| Model input uncertainty | Uncertainty introduced in the selection of final demand sector, value of functional unit, value of margins, and delivery costs. |
| Aggregation uncertainty | Uncertainty due to firms of various sizes utilizing different processes or technology mixes included in the same sector. |
| Imports assumption uncertainty | Uncertainty arising from the assumption that imported commodities are produced using a technology mix identical to that observed in the economy for which the account is being created. A second (less important) source of uncertainty arises from the assumption that each foreign industry produces only one commodity type. |
| Multiplier Uncertainty | Direct and total output results from IO-LCA models are often multiplied by vectors representing impact per unit output. The datasets used to create these multipliers each involve their own uncertainties. Harmonizing between coding systems and data types also introduces error. |

Overview of common uncertainties in single region environmental input-output analysis, reprinted with permission from Hawkins (Hawkins et al.), previously adopted from (Lenzen)

**Table 4**

| Number | OECD Sector | Count | Average | StDev | Min | Max | COV |
|---|---|---|---|---|---|---|---|
| 1 | Agriculture | 19 | 987 | 363 | 398 | 1777 | 0.37 |
| 2 | Energy mining | 4 | 774 | 139 | 577 | 891 | 0.18 |
| 3 | Non-Energy Mining | 7 | 1520 | 608 | 842 | 2678 | 0.40 |
| 4 | Food, Beverages, Tobacco | 34 | 860 | 498 | 219 | 2941 | 0.58 |
| 5 | Textiles and Products | 20 | 675 | 274 | 275 | 1226 | 0.41 |
| 6 | Wood and Products | 9 | 585 | 227 | 418 | 1158 | 0.39 |
| 7 | Pulp, Paper, Products, Publishing | 16 | 698 | 522 | 97 | 1776 | 0.75 |
| 8 | Energy transformation | 5 | 1553 | 609 | 954 | 2427 | 0.39 |
| 9 | Chemicals exc. Pharmaceuticals | 19 | 1834 | 1486 | 336 | 5757 | 0.81 |
| 10 | Pharmaceuticals | 3 | 360 | 202 | 226 | 592 | 0.56 |
| 11 | Rubber and Plastics | 11 | 935 | 166 | 739 | 1219 | 0.18 |
| 12 | Other nonmetal minerals | 17 | 2180 | 2625 | 502 | 11480 | 1.20 |
| 13 | Iron and steel | 3 | 2420 | 1940 | 926 | 4613 | 0.80 |
| 14 | Nonferrous metals | 8 | 1506 | 1023 | 767 | 3940 | 0.68 |
| 15 | Metal Products | 22 | 800 | 292 | 402 | 1553 | 0.37 |
| 16 | Machinery/Equipment NEC | 25 | 540 | 85 | 360 | 718 | 0.16 |
| 17 | Office and computer machinery | 11 | 402 | 98 | 217 | 532 | 0.24 |
| 18 | Electrical machinery NEC | 21 | 583 | 198 | 272 | 1104 | 0.34 |
| 19 | Communication Equipment | 5 | 372 | 176 | 260 | 676 | 0.47 |
| 20 | Medical and Precision equipment | 11 | 331 | 61 | 231 | 439 | 0.19 |
| 21 | Motor Vehicles | 8 | 598 | 95 | 492 | 696 | 0.16 |
| 22 | Ships and Boats | 2 | 424 | 46 | 391 | 457 | 0.11 |
| 23 | Aircraft and Spacecraft | 5 | 348 | 83 | 259 | 483 | 0.24 |
| 24 | Rail Equipment and Transport NEC | 4 | 565 | 107 | 466 | 708 | 0.19 |
| 25 | Other Manufacturing | 25 | 464 | 146 | 208 | 884 | 0.32 |
| 26 | Electricity | 3 | 8675 | 215 | 8545 | 8923 | 0.02 |
| 27 | Gas Distribution | 1 | 700 | | 700 | 700 | |
| 29 | Water Utilities | 1 | 287 | | 287 | 287 | |
| 30 | Construction | 7 | 541 | 59 | 423 | 588 | 0.11 |
| 31 | Wholesale/Retail Trade | 3 | 290 | 125 | 186 | 429 | 0.43 |
| 32 | Hotels and Restaurants | 3 | 453 | 60 | 393 | 514 | 0.13 |
| 33 | Land Transport | 5 | 1355 | 705 | 366 | 2236 | 0.52 |
| 34 | Water Transport | 1 | 2756 | | 2756 | 2756 | |
| 35 | Air Transport | 1 | 1904 | | 1904 | 1904 | |
| 36 | Auxiliary Transport | 1 | 400 | | 400 | 400 | |
| 37 | Post and Telecommunications | 5 | 402 | 467 | 127 | 1233 | 1.16 |
| 38 | Finance and Insurance | 6 | 84 | 18 | 62 | 103 | 0.21 |
| 39 | Real Estate | 1 | 217 | | 217 | 217 | |
| 40 | Machinery/Equip Rental | 3 | 179 | 44 | 146 | 228 | 0.24 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 41 | Computer Activities | 2 | 151 | 21 | 136 | 166 | 0.14 |
| 42 | Research and Development | 1 | 303 | | 303 | 303 | |
| 43 | Other Business Services | 25 | 168 | 83 | 78 | 387 | 0.50 |
| 44 | Government and Defence | 6 | 271 | 162 | 170 | 559 | 0.60 |
| 45 | Education | 3 | 383 | 279 | 168 | 698 | 0.73 |
| 46 | Health and Social Work | 8 | 204 | 64 | 107 | 282 | 0.31 |
| 47 | Other social services | 25 | 258 | 126 | 71 | 557 | 0.49 |
| 48 | Private Households | 2 | 43 | 61 | 0 | 87 | 1.41 |

Comparison of aggregation (Count of 426 sectors aggregated into a single sector and summary statistics of aggregate grouping) of $CO_2$ multipliers (mt $CO_2$/\$M2002) in OECD sectors from 2002 U.S. Benchmark EIO-LCA model. COV = coefficient of variation = standard deviation / mean.

**Table 5**

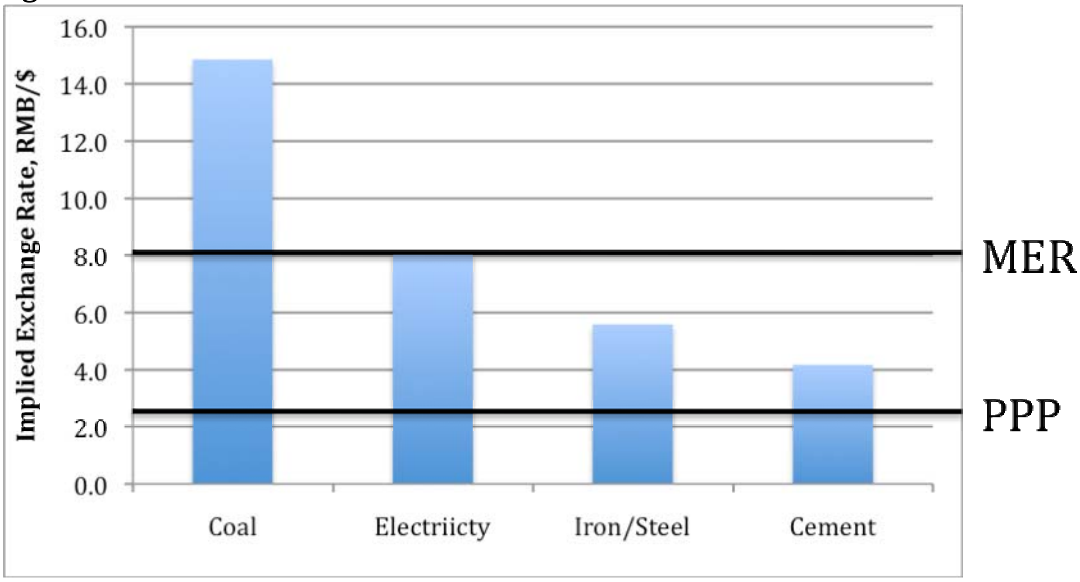
| Number | Sector | Count | Average | Stdev | Min | Max | COV |
|---|---|---|---|---|---|---|---|
| 1 | paddy rice | 1 | 1292 | | 1292 | 1292 | |
| 4 | vegetables/fruits/nuts | 3 | 812 | 8 | 803 | 817 | 0.01 |
| 5 | oilseeds | 1 | 1013 | | 1013 | 1013 | |
| 6 | sugar cane+beet | 1 | 984 | | 984 | 984 | |
| 7 | plant fibers | 1 | 1777 | | 1777 | 1777 | |
| 8 | crops nec | 4 | 1073 | 462 | 689 | 1689 | 0.43 |
| 9 | cattle, sheep and goats | 1 | 1175 | | 1175 | 1175 | |
| 10 | other animals | 2 | 908 | 352 | 659 | 1157 | 0.39 |
| 11 | raw milk | 1 | 964 | | 964 | 964 | |
| 12 | wool, silk | 1 | 879 | | 879 | 879 | |
| 13 | forestry | 2 | 427 | 41 | 398 | 456 | 0.10 |
| 14 | fishing | 1 | 1265 | | 1265 | 1265 | |
| 15 | coal | 1 | 891 | | 891 | 891 | |
| 16 | oil | 3 | 735 | 140 | 577 | 845 | 0.19 |
| 18 | minerals nec | 7 | 1520 | 608 | 842 | 2678 | 0.40 |
| 19 | cattle, sheep and goats | 1 | 934 | | 934 | 934 | |
| 20 | other meat | 2 | 884 | 79 | 829 | 940 | 0.09 |
| 21 | vegetable oils and fats | 3 | 1720 | 1058 | 1074 | 2941 | 0.62 |
| 22 | dairy products | 4 | 805 | 102 | 656 | 881 | 0.13 |
| 23 | processed rice | 1 | 1129 | | 1129 | 1129 | |
| 24 | sugar | 2 | 1826 | 146 | 1723 | 1929 | 0.08 |
| 25 | Other food products | 16 | 683 | 157 | 219 | 971 | 0.23 |
| 26 | bev+tobacco | 5 | 491 | 203 | 236 | 755 | 0.41 |
| 27 | textiles | 12 | 827 | 229 | 448 | 1226 | 0.28 |
| 28 | apparel | 5 | 393 | 93 | 275 | 532 | 0.24 |
| 29 | leather products | 3 | 540 | 206 | 382 | 773 | 0.38 |
| 30 | wood products | 9 | 585 | 227 | 418 | 1158 | 0.39 |
| 31 | paper and publishing | 16 | 698 | 522 | 97 | 1776 | 0.75 |
| 32 | petrol and coal products | 5 | 1553 | 609 | 954 | 2427 | 0.39 |
| 33 | chemicals,rubber,and plastics | 33 | 1400 | 1241 | 226 | 5757 | 0.89 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 34 | other nonmetallic minerals | 17 | 2180 | 2625 | 502 | 11480 | 1.20 |
| 35 | ferrous metals | 3 | 2420 | 1940 | 926 | 4613 | 0.80 |
| 36 | nonferrous metals | 8 | 1506 | 1023 | 767 | 3940 | 0.68 |
| 37 | metal products | 22 | 800 | 292 | 402 | 1553 | 0.37 |
| 38 | motor vehicles and parts | 8 | 598 | 95 | 492 | 696 | 0.16 |
| 39 | other transport equipment | 11 | 441 | 130 | 259 | 708 | 0.30 |
| 40 | electronic equipment | 16 | 393 | 122 | 217 | 676 | 0.31 |
| 41 | machinery+equipment, nec | 57 | 516 | 163 | 231 | 1104 | 0.32 |
| 42 | other manufacturing | 25 | 464 | 146 | 208 | 884 | 0.32 |
| 43 | electricity | 3 | 8675 | 215 | 8545 | 8923 | 0.02 |
| 44 | gas dist | 1 | 700 | | 700 | 700 | |
| 45 | water | 1 | 287 | | 287 | 287 | |
| 46 | construction | 7 | 541 | 59 | 423 | 588 | 0.11 |
| 47 | trdae | 3 | 290 | 125 | 186 | 429 | 0.43 |
| 48 | land,pipe,other transport | 6 | 1196 | 739 | 366 | 2236 | 0.62 |
| 49 | water transport | 1 | 2756 | | 2756 | 2756 | |
| 50 | air transport | 1 | 1904 | | 1904 | 1904 | |
| 51 | post and telecom | 5 | 402 | 467 | 127 | 1233 | 1.16 |
| 52 | financial services | 4 | 85 | 15 | 62 | 97 | 0.18 |
| 53 | insurance | 2 | 83 | 29 | 62 | 103 | 0.35 |
| 54 | business services nec | 32 | 173 | 78 | 78 | 387 | 0.45 |
| 55 | recreational/other services | 28 | 278 | 135 | 71 | 557 | 0.48 |
| 56 | government,education,health | 16 | 258 | 155 | 107 | 698 | 0.60 |
| 57 | owner oc dwellings | 2 | 43 | 61 | 0 | 87 | 1.41 |

Comparison of aggregation (Count of 426 sectors aggregated into a single sector and summary statistics of aggregate grouping) of $CO_2$ multipliers (mt $CO_2$/\$M2002) in OECD sectors from 2002 U.S. Benchmark EIO-LCA model. COV = coefficient of variation = standard deviation / mean.

## Figures:

**Figure 1**




Implied exchange rate calculated using physical unit and monetary output values for 2002 in the U.S. and China, compared to market exchange rate (MER) and purchasing power parity (PPP) rate