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Sectoral Aggregation Error in the Accounting of Energy and Emissions Embodied in Trade and Consumption

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Summary

Correctly accounting for the energy and emissions embodied in consumption and trade is essential to effective climate policy design. Robust methods are needed for both policy making and research—for example, the assignment of border carbon adjustments (BCAs) and greenhouse gas emission reduction responsibilities rely on the consistency and accuracy of such estimates. This analysis investigates the potential magnitude and consequences of the error present in estimates of energy and emissions embodied in trade and consumption. To quantify the error of embodied emissions accounting, we compare the results from the disaggregated Global Trade Analysis Project (GTAP 8) data set, which contains 57 sectors to results from different levels of aggregation of this data set (3, 7, 16, and 26 sectors), using 5,000 randomly generated sectoral aggregation schemes as well as aggregations generated using several commonly applied decisions rules. We find that some commonly applied decision rules for sectoral aggregation can produce a large error. We further show that an aggregation scheme that clusters sectors according to their energy, emissions, and trade intensities (net exports over output) can minimize error in embodied energy and emissions accounting at different levels of aggregation. This sectoral aggregation scheme can be readily used in any input-output analysis and provide useful information for computable general equilibrium modeling exercises in which sector aggregation is necessary, although our findings suggest that, when possible, the most disaggregated data available should be used.

Introduction

Any effective energy and climate policy will require sound accounting procedures. Practitioners often sacrifice data detail in favor of sectoral aggregates for the purpose of assigning reduction burdens based on energy and greenhouse gas emissions (hereafter emissions for brevity) embodied in consumption or trade. Depending on the scheme used, aggregation can introduce large error into emissions accounting (Su et al. 2010). It can misrepresent the potential and limitations of abatement measures and distort the associated costs to parties involved. It is therefore of crucial importance to understand the origins of this error, the factors that affect its magnitude, and aggregation strategies practitioners can adopt to preserve the integrity of emissions accounting.

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Accounting for emissions after aggregating sectors is common practice. Many scholars have discussed the merits of using life cycle emissions embodied in consumption as a basis for allocating responsibility for emissions reductions (e.g., Rose et al. 1998; Kverndokk and Rose 2008; Springmann et al. 2015; Zhang et al. 2016a). Consumption-based emissions are equivalent to conventional territorial production-based emissions minus emissions embodied in net exports. Border carbon adjustments (BCAs) are likewise based on calculations of emissions embodied in a region's net exports. Applications of modeling tools used to support policy decision making also adopt various conventions for aggregating embodied emissions across sectors. However, it is well known that aggregation could lead to errors under certain conditions when the aggregation process involves nonlinear computations. For the case of embodied emissions accounting, matrix inversion is a necessary step, so it will inevitably introduce errors. The same accounting issues apply to embodied energy or material use accounting, which have become more popular with the widely spread idea of life cycle assessment. Therefore, discussions on the embodied emissions accounting in this paper could be easily generalizable to the field of applied energy and industrial ecology (see review articles, e.g., Dixit et al. [2013]).

Our analysis contributes to the literature on embodied emissions by providing generalizable insights on the errors of sectoral aggregation and identifying more robust sector aggregation strategies. Using both algebraic derivation and numerical examples, we clearly show how errors can be introduced by sectoral aggregation: The total emissions intensity of sectors varies significantly across aggregation schemes. With a large-scale Monte-Carlo simulation, we show the size of errors using a commonly used sectoral aggregation scheme under different aggregation levels and test the accuracy of alternative schemes. Our numerical results favor giving equal weights to trade intensity and emission intensity.

The rest of the paper is structured as follows. We first review the literature on sectoral aggregation and the need to understand the origins and magnitude of error as well as methods for limiting its influence. We then develop an analytical framework to illustrate the sources of error in a closed and open economy and discuss whether finer disaggregation is always preferred. We further develop a numerical simulation to show the consequences of increasing levels of aggregation and test the potential of several aggregation rules to minimize error. We conclude the paper by providing some implications of our findings and the ease of implementing aggregation schemes that deliver more robust estimates of embodied emissions. Above all, our results underscore that, when possible, the most disaggregated data should be used.

Literature Review

The use of input-output (I-O) analysis (IOA) to compute indirect factor usage has a long history dating back to Leontief. In the environmental field, it is used to compute full life cycle emission inventories and identify the indirect emissions to be attributed to specific sectors. Multiregional input-output (MRIO) analysis allows the computation of emissions embodied in a country's imports, exports, and consumption (see, e.g., Peters and Hertwich 2008). Similar analysis can be easily extended to embodied energy and material use accounting, and there is a fast-growing literature using the method focusing on specific sectors, including power generation (Wu et al. 2016), residential buildings (Stephan and Stephan 2016), building construction (Gong et al. 2012; Han et al. 2013; Dixit 2017), as well as domestic and international trade (Wiebe et al. 2012; Cui et al. 2015; Su and Ang 2014; Zhang et al. 2016b).

Researchers have very rapidly identified the potential errors caused by the aggregation of sectors when using I-O methods. Early papers (Malinvaud 1954; Theil 1957; Morimoto 1970, and others) have focused on single-country IOA and identified the causes for aggregation error in the output changes caused by changes in final demand.

In a single-country, open economy setting, Feenstra and Hanson (2000) compute the conditions under which aggregation will lead to an error in the factor content of trade. They find the error to be a function of the covariance between trade intensity and factor intensity (share of factor input in total output). In the environmental context, Su and colleagues (2010) find an analytical formula for aggregation error in emissions embodied in trade as well as some empirical estimates which reveal this error to be potentially large, but rapidly decreasing, in the number of included sectors. Lenzen (2011) uses numerical Monte-Carlo analysis and also finds substantial evidence for aggregation error even if the disaggregated dataset is built from imperfect data.

In a MRIO setting, Lenzen and colleagues (2004) have observed that sectoral aggregation can cause significant error in the computation of embodied carbon dioxide (CO_2) trade balances. However, their analysis is based on a small number of countries and only two levels of aggregation, and they do not estimate the error in bilateral flows. Bouwmeester and Oosterhaven (2013) find that substantial errors occur with sectoral and spatial aggregation when estimating embodied CO_2 emissions and water use using the EXIOPOL database. Similarly, de Koning and colleagues (2015) also find that aggregating the original 46 material categories into 16 categories using the EXIOPOL database changes the calculated material footprint of countries by about 30%. Su and Ang (2013) further analyze the effects of competitive imports on the emissions accounting in trade. Steen-Olsen and colleagues (2014) use four global MRIO systems and analyze the sensitivity of a set of aggregate CO_2 multipliers to aggregations in the MRIO. Our analysis complements this literature of aggregation error[1] by providing additional evidence, both algebraically and empirically.

I-O tables (IOTs) also serve for the calibration of multi-sectoral computable general equilibrium (CGE) models, which have been widely used for the analysis of the international implications of climate policy. Doing so requires a data set, such as Global Trade Analysis Project (GTAP) data, which covers both bilateral trade and IOTs for a large number of countries. These models have been extensively used to compute the response of the emissions content of trade to various carbon pricing policies (see Babiker 2005), for example, or to compute BCAs and understand their impacts (see McKibbin and Wilcoxen 2008). Caron (2012) has investigated the potential magnitude of aggregation error which might occur in the general equilibrium estimates of emissions leakage and BCAs. The paper identifies a large error caused by different aggregations of the GTAP data set, and also compares the emissions embodied as estimated by GTAP to those generated with a more disaggregated data set. The paper identifies the error in trade response to be a function of trade intensity and CO_2 intensity at the subsectoral level. Overall, CGE modeling is a field in which aggregation is often required due to computational constraints and could greatly benefit from a systematic assessment of aggregation error and a better understanding of efficient aggregation schemes.

A separate strand of the literature has focused on identifying criteria which can be used to build "optimal" aggregation schemes (which minimize aggregation error). Fisher (1958) identifies criteria for "consistent" aggregation and realizes that the choice of aggregation scheme is bound to depend on the metric of interest (see also Kymn [1990]). Blin and Cohen (1977) and Cabrer and colleagues (1991) develop the idea of using smart clustering approaches which minimize aggregation error by clustering "similar" sectors together. However, their analysis is limited to one-dimensional clustering based on input similarity only. Finally, perhaps closest in spirit to the present paper is Murray (1998), who has implemented a numerical optimization model to identify the optimal aggregation scheme using a numerical solver, similar to the methodology in this paper. However, it deals with an unrealistically small problem and does not consider a multiregional setting. We are unaware of another paper which applies a clustering approach to emissions accounting using a full MRIO data set.

Measuring Error Introduced by Sectoral Aggregation

Given the impossibility of achieving an arbitrarily fine-level sectoral disaggregation, our analysis requires a clear and measurable definition of aggregation error. We define the error associated with sectoral aggregation as the discrepancy between the values of a particular accounting index calculated for the aggregated and original data sets. In this analysis, we focus on emissions embodied in both trade and final consumption. Below, we describe the relevance and origins of aggregation error in closed and open economy settings.

Closed Economy

We first demonstrate that for a closed economy, production- and consumption-embodied emissions are consistent using the I-O inversion approach irrespective of the sectoral aggregation. Here, we consider a closed economy with multiple regions indexed by $r = 1, \ldots, R$ (alias s), multiple sectors indexed by $i = 1, \ldots, I$ (alias j). Let a diagonal matrix $\mathbf{X}$ $((I * R) \times (R * I))$ denote the output matrix, $\mathbf{Z}$ $((I * R) \times (R * I))$ denote the intermediate input matrix, $\mathbf{Y}$ $((I * R) \times 1)$ denote the consumption vector, and ξ $((I * R) \times 1)$ denote the vector $[1 \ldots 1]^T$ (equation 1).

$$\mathbf{y} = (\mathbf{X} - \mathbf{Z})\xi \tag{1}$$

Let $\mathbf{de}$ $((I * R) \times 1)$ denote the direct emissions from production by sector and by region, $\mathbf{ti}$ $((I * R) \times 1)$ denote the total (direct plus indirect) emissions intensity by sector by region, and EP and EC denote total production-based emissions and consumption-based emissions, respectively (equations 2 and 3).

$$EP = \mathbf{de}^{\mathrm{T}}\xi \tag{2}$$

$$EC = \mathbf{ti}^{\mathrm{T}}\mathbf{y} \tag{3}$$

According to the conservation of total emissions, $\mathbf{ti}$ satisfies (equation 4):

$$\mathbf{ti}^{\mathrm{T}}\mathbf{X} = \mathbf{de}^{\mathrm{T}} + \mathbf{ti}^{\mathrm{T}}\mathbf{Z} \tag{4}$$

From equation (4), equation (5):

$$\mathbf{ti}^{\mathrm{T}} = \mathbf{de}^{\mathrm{T}}(\mathbf{X} - \mathbf{Z})^{-1} \tag{5}$$

From equations (1), (2), (3), and (5), equation (6):

$$EC = EP \tag{6}$$

Given that EP does not change when sectors or regions are aggregated together, EC also will not change with sectoral aggregation, an observation made in Lenzen and colleagues (2004). Therefore, total consumption-based emissions are not influenced by the level of sectoral aggregation. However, we should note that the embodied emissions at the detailed sectoral and regional levels, for example, consumption decomposed to household consumption, government consumption, and investment, could be affected by aggregation.

Open Economy

Under an open economy setting, the above relationships do not necessarily hold. We consider an open economy with multiple sectors. Let the diagonal matrix $\mathbf{X}$ $(I \times I)$ denote the output matrix, $\xi (I \times 1)$ denote the vector $[1 \ldots 1]T$, $\mathbf{Z}$ $(I \times I)$ denote the intermediate input matrix ($Z_{i,j}$ represents the use of good from sector i in sector j), $\mathbf{y}$ $(I \times 1)$ denote the consumption vector, and $\mathbf{nx}$ $(I \times 1)$ denote the vector of net exports (equation 7).

$$\mathbf{X}\,\xi = \sum_j z_{i,j} + \mathbf{y} + \mathbf{nx} \tag{7}$$

The matrix $\mathbf{de}$ $(I \times 1)$ denotes the direct emissions from production by sector, while EP, EC, and ENX denote total emissions from production, consumption, and net exports, respectively.

Analogous to (7) equation (8):

$$EP = EC + ENX = \mathbf{de}^{\mathrm{T}}\,\xi \tag{8}$$

We aggregate the sectors with prime superscripts denoting the parameters in the aggregated data set. Using our definition of aggregation error, we calculate differences in production emissions (δ_{EP}), emissions embodied in consumption (δ_{EC}), and emissions embodied in net exports (δ_{ENX}), respectively as: $\delta_{EP} = |EP' - EP|$, $\delta_{EC} = |EC' - EC|$ and $\delta_{ENX} = |ENX' - ENX|$. From equation (8), we know that $\delta_{EP} \equiv 0$. Therefore, $\delta_{EC} = \delta_{ENX}$. In the remaining part of this section, we only focus on δ_{EC}.

From equation (5) above we have equations (9) and (10):

$$\mathbf{ti}^{\mathrm{T}} = \mathbf{de}^{\mathrm{T}}(\mathbf{X} - \mathbf{Z})^{-1} \tag{9}$$

$$\delta_{EC} = \left|EC' - EC\right| = \left|\mathbf{ti}'^{\mathrm{T}}\mathbf{y}' - \mathbf{ti}^{\mathrm{T}}\mathbf{y}\right| \tag{10}$$

To simplify the discussion, we assume that this open economy only consumes one unit from sector 1: $y_1 = 1$ and $y_2 = \ldots = y_I = 0$. Therefore, δ_{EC} is determined by the total emissions intensity of sector 1 from the two data sets as follows:

$$\delta_{EC} = \left|ti_1' - ti_1\right| \tag{11}$$

We then explore the consequences of sectoral aggregation error by showing how total emissions intensity of sector 1 may change upon aggregation.

Effects of Sector Aggregation

We first show that if sector 1 is combined with others (as opposed to being preserved) in the process of aggregation, error can arise in the consumption-embodied emissions through changes in the total emissions intensity of sector 1.

The following 2 × 2 example develops this intuition as follows:

$$\mathbf{X} = \begin{bmatrix} x_1 & 0 \\ 0 & x_2 \end{bmatrix}, \quad \mathbf{Z} = \begin{bmatrix} z_{11} & z_{12} \\ z_{21} & z_{22} \end{bmatrix}, \quad \mathbf{de} = \begin{bmatrix} e_1 \\ e_2 \end{bmatrix}$$

We first compute the total emissions intensity (equation 12):

$$\mathbf{ti}^{\mathrm{T}} = \mathbf{de}^{\mathrm{T}}(\mathbf{X} - \mathbf{Z})^{-1} = \begin{bmatrix} \frac{(x_2 - z_{22})e_1 + z_{21}e_2}{(x_1 - z_{11})(x_2 - z_{22}) - z_{12}z_{21}} \\ \frac{z_{12}e_1 + (x_1 - z_{11})e_2}{(x_1 - z_{11})(x_2 - z_{22}) - z_{12}z_{21}} \end{bmatrix}^{\mathrm{T}} \tag{12}$$

After the two sectors are aggregated, the new total emissions intensity for the aggregated sector can be expressed as follows (equation 13):

$$TI' = \frac{(e_1 + e_2)}{x_1 + x_2 - z_{11} - z_{12} - z_{21} - z_{22}} \tag{13}$$

We can find cases in which $\delta_{EC} = |TI'_1 - TI_1|$ is not always equal to zero (e.g., $\mathbf{X} = \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix}$, $\mathbf{Z} = 0$, $\mathbf{de} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$).

Therefore, error can exist in measures of emissions embodied in consumption after aggregation.

Impact on Sectors That Remain Intact in the Aggregation Process

Even if sector 1 is not aggregated with other sectors during the aggregation process, error may arise in consumption-embodied emissions through changes in the total emissions intensity of the sector 1. We show this situation by a 3 × 3 example as follows (equation 14).

$$\mathbf{X} = \begin{bmatrix} x_1 & 0 & 0 \\ 0 & x_2 & 0 \\ 0 & 0 & x_3 \end{bmatrix}, \mathbf{Z} = \begin{bmatrix} z_{11} & z_{12} & z_{13} \\ z_{21} & z_{22} & z_{23} \\ z_{31} & z_{32} & z_{33} \end{bmatrix}, \mathbf{de} = \begin{bmatrix} e_1 \\ e_2 \\ e_3 \end{bmatrix}$$

$$TI_1 = \frac{e_1\left[(x_2 - z_{22})(x_3 - z_{33}) + z_{22}z_{33}\right] + e_2\left[z_{21}(x_3 - z_{33}) + z_{31}z_{23}\right] + e_3\left[z_{31}(x_2 - z_{22}) + z_{21}z_{32}\right]}{det(\mathbf{X} - \mathbf{Z})} \tag{14}$$

We aggregate sectors 2 and 3 and consider the impact on the total emissions intensity of sector 1. We express the total emissions intensity of sector 1 after aggregation as (equation 15):

$$ti_1' = \frac{e_1(x_2 + x_3 - z_{22} - z_{23} - z_{32} - z_{33}) + (e_2 + e_3)(z_{21} + z_{31})}{det(\mathbf{X}' - \mathbf{Z}')} \tag{15}$$

Given that it is not intuitive to calculate $\delta_{EC} = |\mathrm{ti}_1' - \mathrm{ti}|$, we run the following (equation 16):

$$Max/Min\ ti_1' - ti_1 \tag{16}$$

$$\begin{aligned} s.t. \quad & z_{11} + z_{21} + z_{31} < x_1 \\ & z_{12} + z_{22} + z_{32} < x_2 \\ & z_{13} + z_{23} + z_{33} < x_3 \\ & z_{11} + z_{12} + z_{13} < x_1 \\ & z_{21} + z_{22} + z_{23} < x_2 \\ & z_{31} + z_{32} + z_{33} < x_3 \\ & x_1, x_2, x_3 > 0 \\ & z_{11}, z_{12}, z_{13}, z_{21}, z_{22}, z_{23}, z_{31}, z_{32}, z_{33} \geq 0 \end{aligned}$$

By choosing different initial values, we find that the magnitude of $ti_1' - ti_1$ can range from infinity to negative infinity, which implies that total emissions intensity of the sector, which remains the same after aggregation, could change significantly, suggesting the potential for large error in the calculation of emissions embodied in consumption after aggregation. A numerical example is as below:

$$\mathbf{X} = \begin{bmatrix} 100 & 0 & 0 \\ 0 & 100 & 0 \\ 0 & 0 & 100 \end{bmatrix}, \quad \mathbf{Z} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 99 & 0 & 1 \end{bmatrix},$$

$$\mathbf{de} = \begin{bmatrix} 0 \\ 10000 \\ 1 \end{bmatrix},$$

$$ti_1 = 2, ti_1' = 51.5.$$

The intuition is that when the emission-intensive sector 2 and the less emission-intensive sector 3 are aggregated, the emissions intensity of the aggregated sector becomes higher than that of sector 3. Therefore, sector 1, which highly depends on sector 3, also has higher total emission intensity after aggregation.

More Disaggregated Is Not Always Better

As stated previously, all data are characterized by some level of aggregation in reality. However, it is not necessarily true that a data set which is less aggregated than another data set aggregated from the same original data set will produce a better estimate of embodied emissions. A simple numerical example illustrates the intuition. Starting from a 3×3 matrix, we illustrate a case in which a two-sector aggregation can produce an outcome that is more biased than aggregation to a single sector. Specifically, by aggregating sectors 2 and 3, the resulting embodied emissions are significantly reduced.

$$\mathbf{X} = \begin{bmatrix} 2 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 2 \end{bmatrix}, \quad \mathbf{Z} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}, \quad \mathbf{y} = \begin{bmatrix} 1 & 0 & 1 \end{bmatrix},$$

$$\mathbf{de} = \begin{bmatrix} 0 \\ 0 \\ 10 \end{bmatrix}$$

The resulting aggregation scheme yields consumption-based emissions estimates EC_n for an aggregation at the level of n sectors: $EC_1 = 4$, $EC_2 = 3.33$, $EC_3 = 5$. It is further notable that the discrepancy between the two- and one-sector aggregations is larger than the discrepancy between the three- and one-sector aggregations ($|EC_2 - EC_1| > |EC_3 - EC_1|$). The intuition is that aggregating less emission-intensive sector 2 and emission-intensive sector 3 introduces a large error under the two-sector aggregation, while this error is "countervailed" in the three-sector aggregation when emission-intensive sector 1 is aggregated.

Numerical Example

The magnitude of the error illustrated in the extreme example in the above section raises concerns, but it is not clear whether this error would be large in real-world applications. Therefore, we investigate the extent of error in estimates of total emissions in trade (net exports and bilateral trade) that can emerge through aggregation using an established global energy and economic dataset. We use the Global Trade Analysis Project data set, GTAP 8, which is comprised of consistent national accounts on production and consumption (IOTs) together with bilateral trade flows for 57 sectors and 129 regions for the year 2007 (Narayanan et al. 2012).

Our strategy is as follows. First, we are interested in the magnitude of error associated with the use of an aggregation scheme commonly used in a variety of modeling applications (see, e.g., Paltsev et al. 2005). This scheme is based on grouping together sectors of similar nature (e.g., grouping agricultural goods together). Second, we test aggregation schemes based on alternative criteria to evaluate performance, which we compare to the results of 5,000 randomly generated aggregation schemes[2] as well as the commonly used scheme. This comparison allows us to identify schemes that can be used with greater confidence in global trade-related and consumption-based emissions accounting.

Large Error Is Associated with a Common Aggregation Scheme

We first explore the magnitude of error associated with a commonly used aggregation scheme. This aggregation scheme adopts an intuitive (if somewhat arbitrary) sectoral mapping that attempts to preserve common sectoral classification, for instance, goods associated with agriculture, energy, manufacturing, services, and so on. For our analysis, the GTAP data are aggregated to 26 regions (from 129 regions) to facilitate calculation (see Supporting Information Appendix I available on the Journal's website for the detailed regional list), similar to some modeling practices (e.g., Paltsev et al. 2005). As Su and Ang (2010) have discussed, there is no clear guideline yet for an appropriate spatial aggregation; therefore, we choose 26 regions as the aggregation level because it reasonably simplified the computation while maintaining some regional resolution, which allows us to explore the results for key regions. Regarding sector aggregation, we assume the disaggregated GTAP data set with 57 sectors constitutes the "true" data and use it to develop four aggregated data sets that use a common sectoral mapping and are aggregated at a level of 26, 16, 7, and 3 sectors sequentially (e.g., in Zhang et al. [2013] and Springmann et al. [2015]; see Supporting Information Appendix II on the Web for detailed sectoral mappings).

In this section, we focus on the error of emissions embodied in net exports **ENX** ($R \times 1$) and emissions embodied in bilateral trade **ETR** ($R \times R$) for each region, where R is the set of 26 regions. We note that **ETR** is particularly important in the case of policies focused on emissions embodied in bilateral trade. It is also related to consumption-based emissions because $\delta_{EC} = \delta_{ENX}$ as we have shown in the above section.

The error is measured as the distance between the results generated with the aggregated data set and the original data set. We consider two measures of error: Euclidean and Chebyshev distances. The error of emissions embodied in net exports is measured by Euclidean distance (δ_{ENX_E}) (equation 17)

$$\delta_{ENX_E} = \sqrt{\sum_r \left(\frac{ENX_r{}' - ENX_r}{ENX_r} \right)^2} \tag{17}$$

and the Chebyshev distance (δ_{ENX_C}) (equation 18):

$$\delta_{ENX_C} = \max_r \frac{\left| ENX_r{}' - ENX_r \right|}{ENX_r} \tag{18}$$

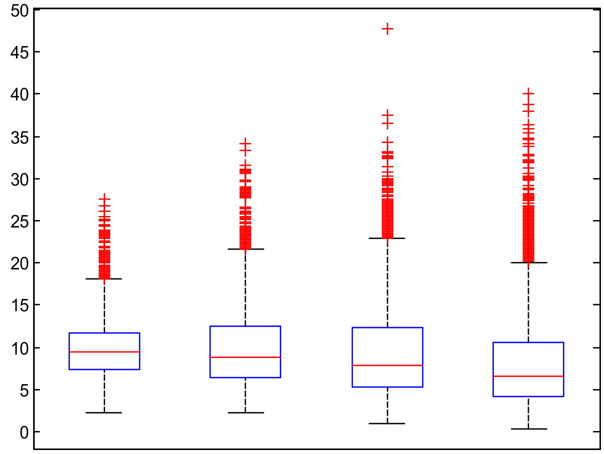

Figure 1 Error in the emissions embodied in net exports measured by Euclidean distance.
Note: From left to right: aggregation to 3, 7, 16, and 26 sectors. The box and whisker plot shows the mean, interquartile, and 95% values of the distance associated with different simulated aggregation strategies.

It is also straightforward to compute the error of emissions embodied in bilateral trade as measured by Euclidean distance (equation 19):

$$\delta_{ETR_E} = \sqrt{\sum_{r,s} \left(\frac{ETR_{r,s}' - ETR_{r,s}}{ETR_{r,s}} \right)^2} \tag{19}$$

And by the Chebyshev distance (equation 20):

$$\delta_{ETR_C} = \max_{r,s} \frac{|ETR_{r,s}' - ETR_{r,s}|}{ETR_{r,s}} \tag{20}$$

Both of these distance measures describe the error associated with sectoral aggregation. Euclidean distance reflects the average error, and Chebyshev distance provides intuitive information about how extreme the error could be for emissions embodied in net export in specific regions or emissions embodied in specific bilateral trade flows.

We also compare δ_{ENX_E}, δ_{ENX_C}, δ_{ETR_E}, and δ_{ETR_C} for each instance of aggregation from the "true" data set using the commonly used scheme and 5,000 randomly generated schemes. We acknowledge that 5,000 is a small number compared to the number of total possible partitions, which can be calculated by using the Stirling number of the second kind S(n,k) as shown in equation (21) (Riordan 1958) (equation 21).[3]

$$S(n, k) = \frac{1}{k!} \sum_{j=0}^{k} (-1)^{k-j} \binom{k}{j} j^n \tag{21}$$

However, this partitioning strategy generates a diverse range of schemes which we believe to be sufficient to assess the relative performance of the common aggregation strategy. It is possible that a larger sample may generate aggregations with smaller error, which means the current analysis may underestimate the relative error and makes the common scheme look better than it otherwise would with a greater number of samples.

Figure 1 shows the distribution of errors in the emissions embodied in net exports measured by Euclidean distance under different aggregation schemes at different aggregation levels. There is a clear trend of decreasing error with the increase of disaggregation level.

We first explore the performance of the commonly used scheme at different aggregation levels using different metrics. Results in table 1 indicate that the performance is in general low with highly aggregated data, but increases significantly when data are more disaggregated. Compared to the original "true" data with 57 sectors, the deviation of emissions embodied in net exports for a certain region using the commonly used scheme could be as high as 13 times the "true" value when the data are aggregated to 16 sectors. For the two largest emitters, China and the United States, the deviations are 9% and 7%. Even if the resolution of data only decreases by about half, that is, from 57 sectors to 26 sectors, the numerical results suggest that the deviation could be more than a factor of 2. Though the deviations for China and the United States decrease to 2% and 0%, respectively, they can be still large for other major countries, for example, 25% for India and 37% for Mexico. Table 1 also shows the percentile (rank) in which the commonly used scheme would fall if the 5000 randomly generated schemes were sorted according to the error they generate. We can also clearly see that the commonly used aggregation performs well compared to a randomly generated aggregation for lower levels of aggregation, especially for the index for emissions embodied in bilateral trade. However, it performs poorly at more aggregated

Table 1 Error and percentile rank of the commonly used scheme using alternative distance measures at three different levels of aggregation

	δ_{ENX_E} *Euclidean Net exports*		δ_{ENX_C} *Chebyshev Net exports*		δ_{ETR_E} *Euclidean Bilateral trade*		δ_{ETR_C} *Chebyshev Bilateral trade*	
	Value	*Rank*	*Value*	*Rank*	*Value*	*Rank*	*Value*	*Rank*
3 sectors	14.44	92.7%	11.43	87.2%	3.55	97.0%	1.67	96.6%
7 sectors	12.24	72.6%	11.05	73.9%	2.68	67.0%	1.75	92.3%
16 sectors	13.97	81.2%	13.83	85.4%	0.70	0.0%	0.30	0.0%
26 sectors	2.34	0.4%	2.26	13.6%	0.41	0.0%	0.18	0.0%

Note: Error defined relative to the "true" 57-sector data set.

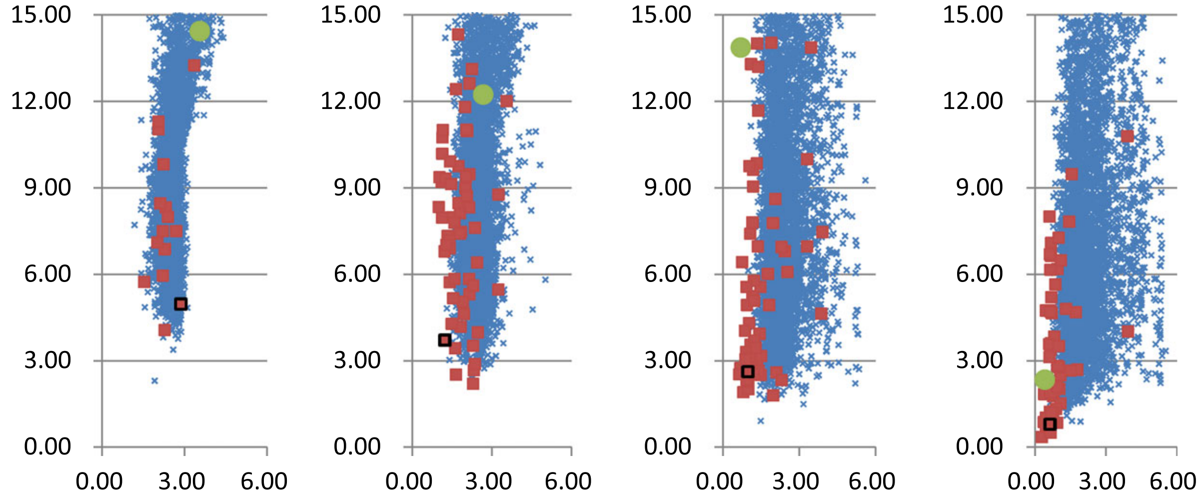

Figure 2 Error in embodied in trade as measured by Euclidean distance.
Note: From left to right: aggregation to 3, 7, 16, 26 sectors. Blue: randomly generated; Red: Clustering; Black square: handpicked most robust scheme; Green: Commonly used. Horizontal axis: δ_{ETR_E}, vertical axis: δ_{ENX_E} (Data with $\delta_{ENX_E} > 15$ not included).

levels. To summarize, the results suggest that using aggregated estimates of emissions embodied in trade to compute the level of tariffs for BCAs can lead to large errors.

Using Clustering to Identify Aggregation Schemes with Reduced Error

The fact that large error can result from common aggregation methods motivates our search for schemes that consistently produce less error across all potential levels of aggregation. A range of criteria exist that we expect could preserve estimates of embodied emissions under a range of aggregation schemes. For instance, sectoral output, trade, CO_2 intensity, and electricity intensity are all indices that, when used to group sectors in the aggregation process, might be expected to preserve the integrity of embodied emissions measures. We perform clustering by applying different weights on these criteria. Comparing the results regarding the embodied emissions measures as above, we identify the clustering schemes with small error and that are robust at all aggregation levels.

We apply output, trade, CO_2 intensity, and electricity intensity as criteria for clustering. For each criterion, we use one vector to reflect different characteristics of different sectors.

Output $\mathbf{v_O}$ (57×1): total output
Trade $\mathbf{v_T}$ (57×1): total trade FOB (Free On Board) value
CO_2 intensity $\mathbf{v_C}$ (57×1): total emissions/total output
Electricity intensity $\mathbf{v_I}$ (57×1): total electricity use/total output

The matrix measuring distances of different sectors under different dimensions consists of the four vectors above (equation 22):

$$\mathbf{X} = [\mathbf{v_O}\ \mathbf{v_T}\ \mathbf{v_C}\ \mathbf{v_I}] \tag{22}$$

We then normalize all the vectors by dividing each element in the vector by the value of the largest element in the vector. Therefore, all the vectors have the maximum value of 1 (equation 23).

$$\bar{\mathbf{X}} = [\overline{\mathbf{v_O}}\ \overline{\mathbf{v_T}}\ \overline{\mathbf{v_C}}\ \overline{\mathbf{v_I}}] \tag{23}$$

We then apply different weight vectors $\mathbf{w}_i$, which we multiply with $\bar{\mathbf{X}}$ (equation 24):

$$\mathbf{w}_i = \begin{bmatrix} w_{O,i} \\ w_{T,i} \\ w_{C,i} \\ w_{I,i} \end{bmatrix} \tag{24}$$

where $w_{O,i}, w_{T,i}, w_{C,i}, w_{I,i} \in [0, 1, 4]$.

Therefore, the matrix used for clustering is as follows (equation 25):

$$\mathbf{X}_i = \bar{\mathbf{X}}\,\mathbf{w}_i \tag{25}$$

Besides $\mathbf{w}_i = 0$ which will have no meaning for clustering, there will be $3^4 - 1 = 80$ types of $\mathbf{w}_i$. Each of them represents one type of criteria for clustering. For example, $\mathbf{w}_i = [4\ 1\ 1\ 0]^T$ means the criterion selected for clustering includes output, trade, and CO_2 intensity, with more weight put on output. We choose the value as 4 because our numerical trials suggest lower or higher values will not usually generate a different aggregation scheme.

Simulation Results

Using a numerical simulation, we first compare the performance of the randomly generated aggregations (blue), aggregations generated using the clustering approach (red), and the commonly used aggregation method (green) shown in figure 2.

We rank the performance of different clustering schemes at different aggregation levels and handpicked the most robust aggregation scheme as being $\mathbf{w}_i = [0\ 1\ 1\ 0]^T$. This result suggests the best criteria selected for clustering includes trade and

CO_2 intensity with the same weights. The finding is in line with Caron (2012), which identified the correlation of trade intensity and CO_2 intensity to be the main determinant of aggregation error in the emissions embodied in trade. A similar conclusion was identified by Feenstra and Hanson (2000) with regard to the error in computation of the factor content of trade.

Conclusions

Climate policy instruments that span across national borders will be most effective and inspire the confidence of signatory nations if they are based on accurate and consistent estimates of embodied emissions. This analysis has demonstrated that the choice of aggregation scheme can introduce and affect the magnitude of error found in embodied emissions estimates. It suggests that, when possible, the most disaggregated data should be used, given that error can increase disproportionately as the level of sector aggregation increases. It further shows that this error can be reduced significantly by employing aggregation criteria that group sectors using the criteria of trade intensity and CO_2 intensity with equal weights. This result is in line with Caron (2012). It is perhaps not surprising that these two criteria emerge as important, given that they are sources of sector heterogeneity that, when pooled together, can mask features of sectors that directly affect emissions embodied in trade and consumption.

Moving to more robust aggregation schemes may be attractive for modelers and policy practitioners, although this choice is not without trade-offs. For modelers who typically aggregate sectors in the process of representing key features of an economy and its response to policy, it may be more important to group sectors to represent key relationships among them, such as substitutability of inputs or outputs or consumer preferences across various categories of consumption. An aggregation scheme that muddles these distinctions will face difficulties to accurately estimate elasticities or long-term trends that govern policy responses or dynamics. An important next step would be to explore if and where the schemes identified here could be combined with structural model requirements. Understanding conditions under which models might produce misleading results would help to avoid such instances and increase confidence in the application of such tools as a basis for policy decisions.

We find that applying intuitive criteria that reflect commonly used economic categorizations can introduce significant error into emissions estimates as sectors are aggregated. These types of aggregation schemes are used in computable general equilibrium models such as Paltsev and colleagues (2005). Our results suggest that the commonly used aggregation performs reasonably well, in line with findings from Su and colleagues (2010) who find that 40 sectors seem to be sufficient to reduce most of the error. Similarly, we find that aggregation to 26 sectors is associated with relatively less severe error. Therefore, for applications that benefit from intuitive mappings that preserve sector input relationships or substitution possibilities (such as CGE modeling), practitioners should preserve as much sectoral detail as possible.

Policy makers and governing bodies involved in setting emissions reduction responsibilities and border penalties can also benefit from improved aggregation schemes, given that more accurate accounting improves the fidelity of the policy signal. However, as in the case of modeling, there is a trade-off associated with determining initial allocations or tariffs based on more robust, but less intuitive, sectoral aggregates (e.g., plasticware could be grouped together with motor oil). Particularly in the case of BCAs, which explicitly assign tariffs based on a calculation of embodied carbon in a sector that was at some point likely aggregated, bureaucracies may be more easily able to handle aggregations that delineate target industries or categories of goods for logistical reasons.

Nevertheless, the potential error of common aggregation strategies should not be ignored, and at least an effort should be made to appreciate the origins and consequences of error and find robust practices for aggregation schemes when aggregation is needed. We recommend the regulating parties build stronger incentives to structure accounting practices in their favor. An important advantage of developing tools and practices for measuring error and raising awareness of the error in embodied emissions accounting is that it will make it more difficult for regulated parties to introduce an error of their own.

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Notes

1. To facilitate the discussion, we focus on sectoral aggregation to illustrate the aggregation error and compare the accuracy of different aggregation schemes. However, as Andrew and colleagues (2009) and Su and Ang (2010) have discussed, spatial aggregation could similarly introduce significant error in the accounting and there is always a trade-off between sectoral and spatial aggregation. Our discussion on the aggregation error and proposed aggregation schemes could be extended to spatial aggregation with additional simulation.
2. Since the main purpose of generating random aggregation schemes is to illustrate the possible range of aggregation errors, we do not impose any constraints (i.e., not allowing one sector aggregated with another sector) for these schemes.
3. The Sterling number is computed as follows: $S(57,26) = 3.5e+52$, $S(57,16) = 3.5e+55$, $S(57,7) = 3.0e+44$, $S(57,3) = 2.6e+26$.

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Supporting Information

Supporting information is linked to this article on the *JIE* website:

Supporting Information S1: This supporting information provides Appendix I, a detailed aggregated region list, and Appendix II, detailed sectoral mappings to develop four aggregated data sets.

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