Title: Sectoral aggregation bias in the accounting of emissions embodied in trade and consumption

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Abstract

Correctly accounting for the emissions embodied in consumption and trade is essential to effective climate policy design. Robust methods are needed for both policy and research—for example, the assignment of border carbon adjustments (BCAs) and emissions reduction responsibilities rely on the consistency and accuracy of such estimates. This analysis investigates the potential magnitude and consequences of the bias present in estimates of emissions embodied in trade and consumption. To quantify the bias 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 dataset (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 bias. We further show that an aggregation scheme that clusters sectors according to their emissions and trade intensities can minimize bias in embodied emissions accounting at different levels of aggregation. This sectoral aggregation principle 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.

Keywords: climate policy; emissions accounting; border carbon adjustments

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1. Introduction

Any effective climate policy will require sound emissions accounting procedures. Yet practitioners often sacrifice data detail in favor of sectoral aggregates for the purpose of assigning reduction burdens based on emissions embodied in consumption or trade. Depending on the scheme used, aggregation can introduce large bias into emissions accounting. 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 bias, the factors that affect its magnitude, and aggregation strategies practitioners can adopt to preserve the integrity of emissions accounting.

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. Consumption-based emissions are equivalent to conventional territorial production-based emissions minus emissions embodied in net exports within a given region. 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.

This analysis provides generalizable insights on the pitfalls of sectoral aggregation for embodied emissions accounting and identifies more robust sector aggregation strategies. The paper is structured as follows. Section 2 reviews the literature on sectoral aggregation and the need to understand the origins and magnitude of bias as well as methods for limiting its influence. Section 3 develops an analytical framework to illustrate the sources of bias in a closed and open economy, and discusses whether a finer disaggregation is always preferred. Section 4 develops a numerical simulation to show the consequences at increasing levels of aggregation, and tests several aggregation rules for minimizing bias. Section 5 discusses the implications of our findings and the ease of implementing aggregation schemes that deliver superior estimates of embodied emissions. Above all, our results underscore that when possible, the most disaggregated data should be used.

2. Literature review

The use of input-output analysis 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. Multi-regional input-output (MRIO) analysis allows the computation of the amount of emissions embodied in a country's imports, exports, and consumption (see for example Peters and Hertwich 2008).

Researchers have very rapidly identified the potential biases caused by the aggregation of sectors when using input-output methods. Early papers (Malinvaud 1954, Theil 1957, Morimoto 1970, and others) have focused on single-country input-output analysis and identified the causes for aggregation bias 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 a bias in the factor content of trade. They find the bias to be a function of the covariance between trade intensity (net exports over output) and factor intensity. In the environmental context, Su et al. (2010) find an analytical formula for aggregation bias in emissions embodied in trade as well as a number of empirical estimates which reveal this bias to be potentially large, but rapidly decreasing in the number of included sectors. Linzen (2011) uses numerical Monte-carlo analysis and also finds substantial evidence for aggregation bias even if the disaggregated dataset is built from imperfect data.

In a multi-regional input-output (MRIO) setting, Lenzen, Pade and Munksgaard (2004) have observed that sectoral aggregation can cause significant bias in the computation of embodied CO_2 trade balances. However, their analysis is based on small number of countries and only two levels of aggregation, and they do not estimate the bias in bilateral flows.

Input-output tables 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 dataset, such as GTAP, which covers both bilateral trade and input-output tables 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 bias which might occur in the general equilibrium estimates of emissions leakage and BCAs. The paper identifies a large bias caused by different aggregations of the GTAP dataset, and also compares the emissions embodied as estimated by GTAP to those generated with a more disaggregated dataset. The paper identifies the bias in trade response to be a function of trade intensity and CO_2 intensity at the sub-sectoral 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 bias 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 bias). Fischer (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 et al (1991) develop the idea of using smart clustering approaches which minimize aggregation bias 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 multi-regional setting. We are unaware of another paper which applies a clustering approach to emissions accounting using a full MRIO dataset.

3. Measuring bias 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 bias. We define the bias associated with sectoral aggregation in terms of 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 bias in closed and open economy settings.

3.1 Closed economy

We first demonstrate that for a closed economy, production- and consumption-embodied emissions are consistent using the input-output 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 **Y** $((I * R) \times (R * I))$ denote the output matrix, $\mathbf{A}$ $((I * R) \times (R * I))$ denote the intermediate input matrix, **C** $((I * R) \times 1)$ denote the consumption vector, and $\boldsymbol{\xi}$ $((I * R) \times 1)$ denote the vector $[1 \quad \ldots \quad 1]^T$.

(1) $$\mathbf{C} = (\mathbf{Y} - \mathbf{A})\boldsymbol{\xi}$$

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.

(2) $$EP = \mathbf{DE}^\mathbf{T}\boldsymbol{\xi}$$

(3) $$EC = \mathbf{TI}^\mathbf{T}\mathbf{C}$$

According to the MRIO relationship, $\mathbf{TI}$ satisfies:

(4) $$\mathbf{TI}^\mathbf{T}\mathbf{Y} = \mathbf{DE}^\mathbf{T} + \mathbf{TI}^\mathbf{T}\mathbf{A}$$

From (4),

(5) $$\mathbf{TI}^\mathbf{T} = \mathbf{DE}^\mathbf{T}(\mathbf{Y} - \mathbf{A})^{-1}$$

From (1), (2), (3) and (5)

(6) $$EC = EP$$

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 Linzen et al. (2004). Therefore, total consumption-based emissions are not influenced by the level of sectoral aggregation.

3.2 Open economy

Moving to an open economy setting, the above relationships do not necessarily hold. We consider an open economy with multiple sectors. Let the diagonal matrix $\mathbf{Y}$ $(I \times I)$ denote the output matrix, $\mathbf{A}$ $(I \times I)$ denote the intermediate input matrix ($A_{i,j}$ represents the use of good from sector i in sector j), $\mathbf{C}$ $(I \times 1)$ denote the consumption vector, and $\mathbf{NX}$ $(I \times 1)$ denote the vector of net exports.

(7) $$\mathbf{Y}\,\boldsymbol{\xi} = \textstyle\sum_j A_{i,j} + \mathbf{C} + \mathbf{NX}$$

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),

(8) $$EP = EC + ENX = \mathbf{DE}^{\mathbf{T}}\boldsymbol{\xi}$$

We perform the sector aggregation, with prime superscripts denoting the parameters in the aggregated dataset. Using our definition for bias above, we calculate total emissions from production (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 (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 (5) above we have (9):

(9) $$\mathbf{TI}^{\mathbf{T}} = \mathbf{DE}^{\mathbf{T}}(\mathbf{Y} - \mathbf{A})^{-1}$$

(10) $$\delta_{EC} = |EC' - EC| = |\mathbf{TI'}^{\mathbf{T}}\mathbf{C}' - \mathbf{TI}^{\mathbf{T}}\mathbf{C}|$$

To simplify the discussion we assume this open economy only consumes one unit of a single good from sector 1: $C_1 = 1$ and $C_2 = \cdots = C_I = 0$. Therefore, δ_{EC} is determined by the total emissions intensity of sector 1 from the two data sets as follows:

(11) $$\delta_{EC} = |TI'_1 - TI_1|$$

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

3.2.1 Effects of sector aggregation

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

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

$\mathbf{Y} = \begin{bmatrix} y_1 & 0 \\ 0 & y_2 \end{bmatrix}$, $\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$, $\mathbf{DE} = \begin{bmatrix} e_1 \\ e_2 \end{bmatrix}$

We first compute the total emissions intensity:

$$(12) \qquad \mathbf{TI^T} = \mathbf{DE^T}(\mathbf{Y} - \mathbf{A})^{-1} = \begin{bmatrix} \frac{(y_2 - a_{22})e_1 + a_{21}e_2}{(y_1 - a_{11})(y_2 - a_{22}) - a_{12}a_{21}} \\ \frac{a_{12}e_1 + (y_1 - a_{11})e_2}{(y_1 - a_{11})(y_2 - a_{22}) - a_{12}a_{21}} \end{bmatrix}^{\mathrm{T}}$$

After the two sectors are aggregated the new total emissions intensity for the aggregated sector can be expressed as follows:

$$(13) \qquad TI' = \frac{(e_1 + e_2)}{y_1 + y_2 - a_{11} - a_{12} - a_{21} - a_{22}}$$

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

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

3.2.2 Impact on sectors that remain intact in the aggregation process

Even if sector 1 is not aggregated together with other sectors as part of the aggregation process, the bias may also arise in the consumption-embodied emissions measure through changes in the total emissions intensity of the sector 1.
This can be expressed for a 3×3 example as follows.

$\mathbf{Y} = \begin{bmatrix} y_1 & 0 & 0 \\ 0 & y_2 & 0 \\ 0 & 0 & y_3 \end{bmatrix}$, $\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}$, $\mathbf{DE} = \begin{bmatrix} e_1 \\ e_2 \\ e_3 \end{bmatrix}$.

$$(14) \qquad TI_1 = \frac{e_1[(y_2 - a_{22})(y_3 - a_{33}) + a_{22}a_{33}] + e_2[a_{21}(y_3 - a_{33}) + a_{31}a_{23}] + e_3[a_{31}(y_2 - a_{22}) + a_{21}a_{32}]}{det(\mathbf{Y} - \mathbf{A})}$$

We aggregate sector 2 and 3, and consider the impact on the total emissions intensity of sector 1. We express total emissions intensity of sector 1 after aggregation as*:*

$$(15) \qquad TI_1' = \frac{e_1(y_2 + y_3 - a_{22} - a_{23} - a_{32} - a_{33}) + (e_2 + e_3)(a_{21} + a_{31})}{det(\mathbf{Y'} - \mathbf{A'})}$$

Given that it is not intuitive to calculate $\delta_{EC} = |\mathrm{TI'}_1 - \mathrm{TI}_1|$, we run the following

$$(16) \qquad \begin{aligned} & Max/Min\, TI_1' - TI_1 \\ s.t. \quad & a_{11} + a_{21} + a_{31} < y_1 \\ & a_{12} + a_{22} + a_{32} < y_2 \\ & a_{13} + a_{23} + a_{33} < y_3 \\ & y_1, y_2, y_3 > 0 \end{aligned}$$

$$a_{11}, a_{12}, a_{13}, a_{21}, a_{22}, a_{23}, a_{31}, a_{32}, a_{33} \geq 0$$

By choosing some initial values we find that the magnitude of $TI_1' - TI_1$ ranges 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 bias in the calculation of emissions embodied in consumption after aggregation. A numerical example is as below:

$$\mathbf{Y} = \begin{bmatrix} 10000 & 0 & 0 \\ 0 & 10000 & 0 \\ 0 & 0 & 10000 \end{bmatrix}, \mathbf{A} = \begin{bmatrix} 0 & 0 & 0 \\ 1 & 1 & 1 \\ 9998 & 9998 & 9998 \end{bmatrix}, \mathbf{DE} = \begin{bmatrix} 1 \\ 10000 \\ 1 \end{bmatrix},$$

$TI_1 = 2,\ TI_1' = 5000.$

3.3 More disaggregated is not always better

As stated previously, in reality all data is characterized by some level of aggregation. However, it is not necessarily true that an aggregated data set which is more disaggregated than another data set aggregated from the same original data set will produce a closer 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.

$$\mathbf{Y} = \begin{bmatrix} 2 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 2 \end{bmatrix}, \mathbf{A} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}, \mathbf{C} = \begin{bmatrix} 1 & 0 & 1 \end{bmatrix}, \mathbf{DE} = \begin{bmatrix} 0 \\ 0 \\ 10 \end{bmatrix}$$

The resulting aggregation scheme yields consumption-based emissions estimates EC_n for an aggregation at the level of n sectors of $EC_1 = 4$, $EC_2 = 3.33$, $EC_3 = 5$. 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 ($|EC_2 - EC_1| > |EC_3 - EC_1|$).

4. Numerical example

The magnitude of the bias illustrated in the extreme example at the end of Section 3.2.2 raises concerns, but it is not clear whether this bias would be large in real-world applications. We therefore investigate the extent of bias 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 (input-output tables) together with bilateral trade flows for 57 sectors and 129 regions for the year 2007 (Narayanan, Betina, & Robert, 2012; Narayanan, 2012).

Our strategy is as follows. First, we are interested in the magnitude of bias associated with the use of an aggregation scheme commonly-used in a variety of modeling applications (see for example Paltsev et al., 2005). This scheme is based on grouping together sectors of similar nature (grouping agricultural goods together, for example). 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 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.

4.1 Large bias is associated with a common scheme

We first explore the magnitude of bias 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, service and so on. For our analysis, the GTAP data is aggregated to 26 regions (from 129 regions) to facilitate calculation (see Appendix I for the detailed regional list). 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 (see Appendix II for detailed sectoral mappings).

In this section, we focus on the bias of emissions embodied in net exports **ENX** $(R \times 1)$ and emissions embodied in bilateral trade **ETR** $(R \times R)$ for each region. 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 Section 3.2.

The bias is measured as a distance between the results from the aggregated data set and the original data set. We consider two measures of bias, Euclidean and Chebyshev distances. The bias of emissions embodied in net exports is measured by Euclidean distance (δ_{ENX_E}) as follows:

$$(17) \quad \delta_{ENX\_E} = \sqrt{\sum_r \left(\frac{ENX_r{}' - ENX_r}{ENX_r}\right)^2}$$

And by the Chebyshev distance (δ_{ENX_C}):

$$(18) \quad \delta_{ENX\_C} = \max_r \frac{|ENX_r{}' - ENX_r|}{ENX_r}$$

It is also straightforward to calculate the bias of emissions embodied in bilateral trade as measured by Euclidean distance:

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

And by the Chebyshev distance:

$$(20) \quad \delta_{ETR\_C} = \max_{r,s} \frac{|ETR_{r,s}{}' - ETR_{r,s}|}{ETR_{r,s}}$$

Each of these distance measures provides an indicator of bias associated with sectoral aggregation. Euclidean distance reflects the bias from the average aspect and Chebyshev distance provides intuitive information about how extreme the bias could be for emissions embodied in net export for a certain region or emissions embodied in a certain bilateral trade flow.

We also compare δ_{ENX_E}, δ_{ENX_C}, δ_{ETR_E} and δ_{ETR_C} for each instance of aggregation from the "true" dataset using the commonly-used scheme and 5,000 randomly generated schemes. We acknowledge that 5,000 is a small number compare to the number of total possible partitions calculated by using the Stirling number of the second kind S(n,k) as shown in equation (21).[1]

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

However, this partition strategy generates a diverse range of samples 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 bias, which means the current analysis may underestimate the relative bias and makes the common scheme look better than it otherwise would with a greater number of samples.

The results for four data sets that have been aggregated using common schemes are shown below:

Table 1 Value and percentile rank using alternative distance measures at three different levels of aggregation and the "original" data set.

	$\boldsymbol{\delta_{ENX\_E}}$		$\boldsymbol{\delta_{ENX\_C}}$		$\boldsymbol{\delta_{ETR\_E}}$		$\boldsymbol{\delta_{ETR\_C}}$	
	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%

As shown in Table 1, as we move from δ_{ENX_E} and δ_{ETR_E}, we find the average bias clearly falls as the level of aggregation decreases. However, δ_{ENX_C} and δ_{ETR_C} are still generally decreasing (except for the transition from 16 to 7 sectors for δ_{ENX_C}**)**. Moreover, from the order of magnitude of δ_{ENX_C}, we find that the bias for emissions embodied in net exports for a certain region could be large. Compared to the original "true" data with 57 sectors, the deviation of emissions embodied in net exports for a certain region could be about 11 times the "true" value when the data is aggregated to 3 sectors. Even if the resolution of data only decreases by about half, e.g. from 57 sectors to 26 sectors, the numerical results suggest that the deviation could be over two times as large. This shows that using aggregated estimates of emissions embodied in trade to compute the level of tariffs for BCAs can lead to large errors.

[1] 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.

The Table also shows the percentile (rank) in which the common aggregation scheme would fall if schemes were sorted according to the bias they generate. When looking at the rank, we find 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 levels.

4.2 Using clustering to identify aggregation schemes with reduced bias

The fact that large bias can result from common aggregation methods motivates our search for schemes that consistently produce less biased aggregations 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, 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 in terms of the embodied emissions measures as above, we select the clustering schemes with small bias 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 above four vectors:

$$\mathbf{X} = [\mathbf{V_O}\ \mathbf{V_T}\ \ \mathbf{V_C}\ \ \mathbf{V_I}\ ]$$

Then we normalize all the vectors by dividing each element in the vector by the value of largest element in the vector. Therefore, all the vectors have the maximum value of 1.

$$\overline{\mathbf{X}} = [\overline{\mathbf{V_O}}\ \overline{\mathbf{V_T}}\ \ \overline{\mathbf{V_C}}\ \ \overline{\mathbf{V_I}}\ ]$$

We then apply different weight vector $\mathbf{W}_i$ multiplying with $\overline{\mathbf{X}}$.

$$\mathbf{W}_i = \begin{bmatrix} W_{O,i} \\ W_{T,i} \\ W_{C,i} \\ W_{I,i} \end{bmatrix}$$

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

Therefore, the matrix used for clustering is as follows:

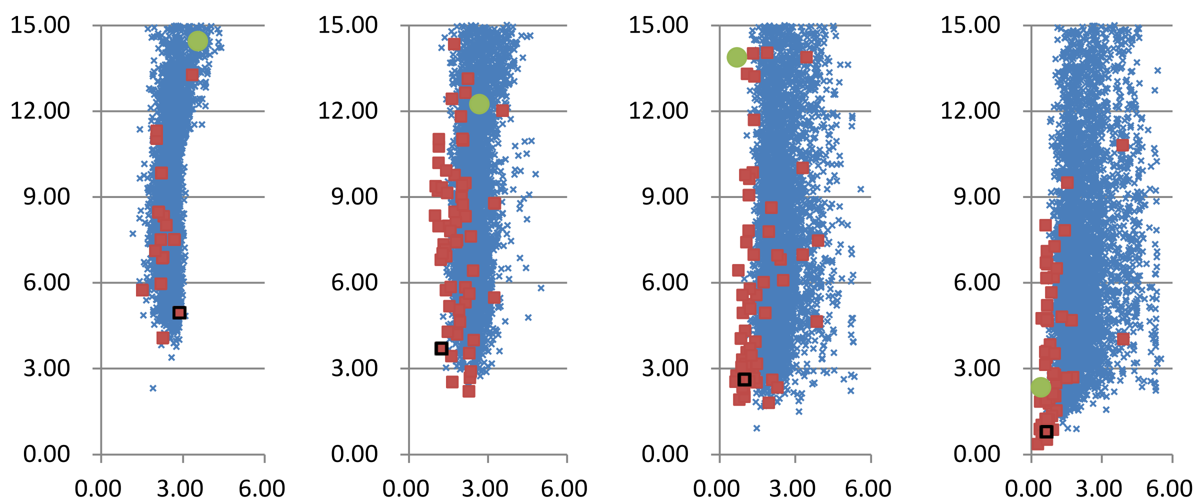
$$\mathbf{X}_i = \bar{\mathbf{X}}\mathbf{W}_i$$

Besides $\mathbf{W}_\mathrm{i} = 0$ which will have no meaning for clustering, there will be $3^4 - 1 = 80$ types of $\mathbf{W}_\mathrm{i}$. Each of them represents one type of criteria for clustering. For example, $\mathbf{W}_\mathrm{i} = [4\ \ 1\ \ 1\ \ 0]^\mathrm{T}$ means criteria selected for clustering includes output, trade and CO^2 intensity, with more weight put on output.

4.2.1 Results

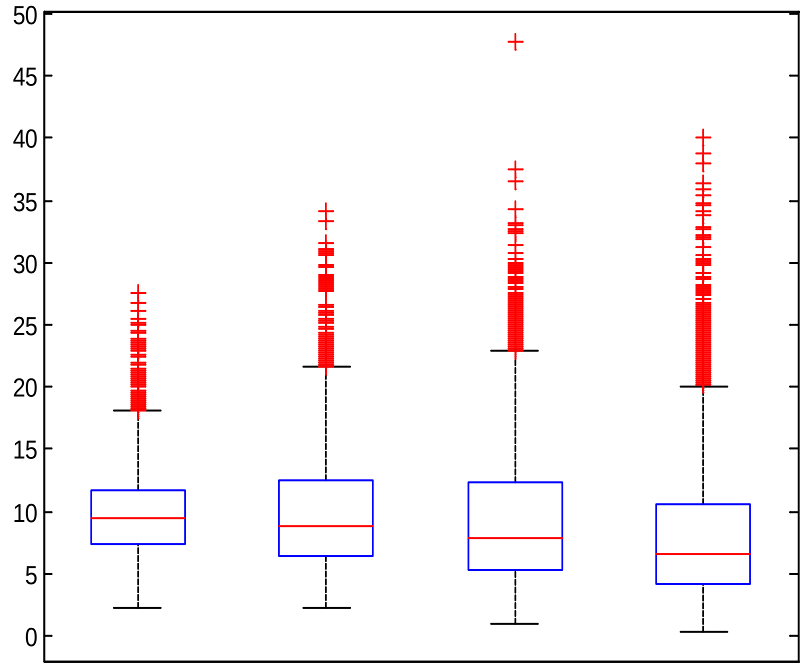
Using a numerical simulation, we first compare the performance of the randomly generated aggregations (blue), aggregations generated using the clustering approach (red), and the commonly-used aggregation method (green).

Figure 1 Bias of emissions embodied in trade as measured by Euclidean distance. From left to right: aggregation to 3, 7, 16, 26 sectors. Blue: randomly-generated; Red: Clustering (with black box: the robust one); Green: Commonly-used. Horizontal axis: δ_{ETR_E} (Data with $\delta_{ETR\_E} > 15$ not included) Vertical axis: δ_{ENX_E}



The most robust aggregation scheme is $\mathbf{W}_\mathrm{i} = [0\ \ 1\ \ 1\ \ 0]^\mathrm{T}$, which means the best criteria selected for clustering includes trade and CO_2 intensity with the same weights. This 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 bias in the emissions embodied in trade. A similar conclusion was identified by Feenstra and Hanson (2000) w.r.t. to the bias in computation of the factor content of trade.

Figure 2 Bias of emissions embodied in net exports measured by Euclidean distance. From left to right: aggregation to 3, 7, 16, 26 sectors. The box and whisker plot shows the mean, interquartile, and 95% values of the distance associated with different simulated aggregation strategies.



5. 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 bias found in embodied emissions estimates. It suggests that when possible, the most disaggregated data should be used, given that bias can increase disproportionately as the level of sector aggregation increases. It further shows that this bias 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 these more robust aggregation schemes may be attractive for modelers and policy practitioners, although this choice is not without tradeoffs. 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 in order 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 difficultly in cleanly estimating 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 result introduce significant bias into emissions estimates as sectors are aggregated. These types of aggregation schemes are used in computable general equilibrium models such as Paltsev et al. (2005). Our results suggest that the commonly-used aggregation performs reasonably well, in line with findings from Lenzen et al. (2004) who find that 40 sectors seems to be sufficient to reduce most of the bias. Similarly, we find that aggregation to 26 sectors is associated with relatively less severe bias. 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.

Policymakers 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 tradeoff associated with determining initial allocations or tariffs based on more robust but less intuitive sectoral aggregates (for instance plastic ware 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 bias of common strategies should not be ignored, and at least an effort should be made to appreciate the origins and consequences of bias for research and policy. One reason for this awareness is obvious. Parties bound by regulation have strong incentives to structure accounting practices in their favor. An important advantage of tools and practices for measuring bias, and raising awareness of its role in embodied emissions accounting, is that it will make it more difficult for regulated parties to introduce a bias of their own.

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Appendix I:

Detailed Aggregated Region List

Abbreviation	**Regions aggregated**
ANZ	Australia and New Zealand
ARG	Argentina
ASI	Other Asian countries
BRA	Brazil
CAN	Canada
CHN	China and Hong Kong
DEU	Germany
FRA	France
FSU	Formal Soviet Union leftovers
GBR	United Kingdom
IDN	Indonesia
IND	India
ITA	Italy
JPN	Japan
KOR	South Korea
LAM	Latin America
MEN	Middle East and North Africa
MEX	Mexico
REU	Rest of Europe
ROW	Mainly Former Soviet Union Countries and Balkan countries
RUS	Russian Federation
SSA	Sub-Saharan Africa
TSG	Taiwan and Singapore
TUR	Turkey
USA	United States
ZAF	South Africa

Appendix II:

Detailed sectoral mappings to develop four aggregated data sets at a level of 26, 16, 7 and 3 sectors based on commonly-used rules

(a) 57 to 3 sectors

Abbreviation	**Description**	**Description of aggregated sectors**
PDR	Paddy rice	Agriculture
WHT	Wheat	
GRO	Cereal grains nec	
V_F	Vegetables fruit nuts	
OSD	Oil seeds	
C_B	Sugar cane sugar beet	
PFB	Plant-based fibers	
OCR	Crops nec	
CTL	Bovine cattle sheep and goats horses	
OAP	Animal products nec	
RMK	Raw milk	
WOL	Wool silk-worm cocoons	
FRS	Forestry	
FSH	Fishing	
CMT	Bovine meat products	
OMT	Meat products nec	
VOL	Vegetable oils and fats	
MIL	Dairy products	
PCR	Processed rice	
SGR	Sugar	
COA	Coal	Mining, manufacturing, trade, construction and transport
OIL	Crude Oil	
GAS	Gas	
OMN	Minerals nec	
OFD	Food products nec	
B_T	Beverages and tobacco products	
TEX	Textiles	
WAP	Wearing apparel	
LEA	Leather products	
LUM	Wood products	
PPP	Paper products publishing	
P_C	Petroleum and coal products	
CRP	Chemical rubber plastic products	
NMM	Mineral products nec	
I_S	Ferrous metals	
NFM	Metals nec	
FMP	Metal products	

MVH	Motor vehicles and parts	
OTN	Transport equipment nec	
ELE	Electronic equipment	
OME	Machinery and equipment nec	
OMF	Manufactures nec	
ELY	Electricity	
GDT	Gas manufacture distribution	
WTR	Water	
CNS	Construction	
TRD	Trade	
OTP	Transport nec	
WTP	Water transport	
ATP	Air transport	
CMN	Communication	Service
OFI	Financial services nec	
ISR	Insurance	
OBS	Business services nec	
ROS	Recreational and other services	
OSG	Public administration, defense, education and health	
DWE	Dwellings	

(b) 57 to 7 sectors

Abbreviation	Description	Description of aggregated sectors
PDR	Paddy rice	Agriculture
WHT	Wheat	
GRO	Cereal grains nec	
V_F	Vegetables fruit nuts	
OSD	Oil seeds	
C_B	Sugar cane sugar beet	
PFB	Plant-based fibers	
OCR	Crops nec	
CTL	Bovine cattle sheep and goats horses	
OAP	Animal products nec	
RMK	Raw milk	
WOL	Wool silk-worm cocoons	
FRS	Forestry	
FSH	Fishing	
CMT	Bovine meat products	
OMT	Meat products nec	
VOL	Vegetable oils and fats	
MIL	Dairy products	
PCR	Processed rice	
SGR	Sugar	
COA	Coal	Primary energy production (coal)
OIL	Crude Oil	Primary energy production (crude oil, gas) and others
GAS	Gas	
OMN	Minerals nec	
P_C	Petroleum and coal products	Secondary energy production
ELY	Electricity	
GDT	Gas manufacture distribution	
OFD	Food products nec	Light manufacturing industry
B_T	Beverages and tobacco products	
TEX	Textiles	
WAP	Wearing apparel	
LEA	Leather products	
LUM	Wood products	
PPP	Paper products publishing	
FMP	Metal products	
MVH	Motor vehicles and parts	
OTN	Transport equipment nec	
ELE	Electronic equipment	
OME	Machinery and equipment nec	
OMF	Manufactures nec	

WTR	Water	
CRP	Chemical rubber plastic products	Heavy manufacturing industry, construction and transport
NMM	Mineral products nec	
I_S	Ferrous metals	
NFM	Metals nec	
CNS	Construction	
OTP	Transport nec	
WTP	Water transport	
ATP	Air transport	
TRD	Trade	Trade and service
CMN	Communication	
OFI	Financial services nec	
ISR	Insurance	
OBS	Business services nec	
ROS	Recreational and other services	
OSG	Public administration, defense, education and health	
DWE	Dwellings	

(c) 57 to 16 sectors

Abbreviation	Description	Description of aggregated sectors
PDR	Paddy rice	Agriculture
WHT	Wheat	
GRO	Cereal grains nec	
V_F	Vegetables fruit nuts	
OSD	Oil seeds	
C_B	Sugar cane sugar beet	
PFB	Plant-based fibers	
OCR	Crops nec	
CTL	Bovine cattle sheep and goats horses	
OAP	Animal products nec	
RMK	Raw milk	
WOL	Wool silk-worm cocoons	
FRS	Forestry	
FSH	Fishing	
CMT	Bovine meat products	
OMT	Meat products nec	
VOL	Vegetable oils and fats	
MIL	Dairy products	
PCR	Processed rice	
SGR	Sugar	
COA	Coal	Coal
OIL	Crude Oil	Crude oil
GAS	Gas	Gas
OMN	Minerals nec	Other mining
P_C	Petroleum and coal products	Petroleum and coal products
OFD	Food products nec	Light manufacturing industry I
B_T	Beverages and tobacco products	
TEX	Textiles	
WAP	Wearing apparel	
LEA	Leather products	
LUM	Wood products	
PPP	Paper products publishing	
FMP	Metal products	Light manufacturing industry II
MVH	Motor vehicles and parts	
OTN	Transport equipment nec	
ELE	Electronic equipment	
OME	Machinery and equipment nec	
OMF	Manufactures nec	
CRP	Chemical rubber plastic products	Heavy manufacturing industry II
NMM	Mineral products nec	

I_S	Ferrous metals	
NFM	Metals nec	
ELY	Electricity	Electricity
GDT	Gas manufacture distribution	Gas manufacture distribution
WTR	Water	Water
CNS	Construction	Construction
TRD	Trade	Trade
OTP	Transport nec	Transport
WTP	Water transport	
ATP	Air transport	
CMN	Communication	Service
OFI	Financial services nec	
ISR	Insurance	
OBS	Business services nec	
ROS	Recreational and other services	
OSG	Public administration, defense, education and health	
DWE	Dwellings	

(d) 57 to 26 sectors (C-REM model applies)

Abbreviation	**Description**	**Description of aggregated sectors**
PDR	Paddy rice	Agriculture
WHT	Wheat	
GRO	Cereal grains nec	
V_F	Vegetables fruit nuts	
OSD	Oil seeds	
C_B	Sugar cane sugar beet	
PFB	Plant-based fibers	
OCR	Crops nec	
CTL	Bovine cattle sheep and goats horses	
OAP	Animal products nec	
RMK	Raw milk	
WOL	Wool silk-worm cocoons	
FRS	Forestry	
FSH	Fishing	
CMT	Bovine meat products	
OMT	Meat products nec	
VOL	Vegetable oils and fats	
MIL	Dairy products	
PCR	Processed rice	
SGR	Sugar	
COA	Coal	Coal
OIL	Crude Oil	Crude oil
GAS	Gas	Gas
OMN	Minerals nec	Other mining
OFD	Food products nec	Food, beverages and tobacco
B_T	Beverages and tobacco products	
TEX	Textiles	Textiles
WAP	Wearing apparel	Clothing
LEA	Leather products	
LUM	Wood products	Wood products
PPP	Paper products publishing	Paper products publishing
P_C	Petroleum and coal products	Petroleum and coal products
CRP	Chemical rubber plastic products	Chemicals
NMM	Mineral products nec	Mineral products
I_S	Ferrous metals	Ferrous and non-ferrous metals
NFM	Metals nec	
FMP	Metal products	Metal products
MVH	Motor vehicles and parts	Vehicle and transport equipment
OTN	Transport equipment nec	
ELE	Electronic equipment	Electronic equipment

OME	Machinery and equipment nec	Machinery
OMF	Manufactures nec	Other manufactures
ELY	Electricity	Electricity
GDT	Gas manufacture distribution	Gas manufacture distribution
WTR	Water	Water
CNS	Construction	Construction
TRD	Trade	Trade
OTP	Transport nec	Transport
WTP	Water transport	
ATP	Air transport	
CMN	Communication	Service
OFI	Financial services nec	
ISR	Insurance	
OBS	Business services nec	
ROS	Recreational and other services	
OSG	Public administration, defense, education and health	
DWE	Dwellings	