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# Harnessing the Power of Input-Output Analysis for Sustainability[1]

## Simulation based on US data to inform aggregate statistics

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**Abstract**

Measuring carbon contents reliably, for products, firms and industries, is key for identifying transition risks. The new G20 Data Gaps Initiative asks for collecting emission data and multiregional IO tables to enable the calculation of aggregate carbon contents. What sectoral distinctions do we need, what level of granularity? What is the role of international linkages? Do we need information on technology? How can statistical data be used in carbon accounting? Based on IO tables and company level data from the United States, I build up a micro simulation environment that can act as a laboratory for answering these questions. The data base consists of almost 5000 units located in the United States and enables a rather complete tracking of private economy value chains. The analysis takes a focus on indirect emissions and carbon contents.

First results indicate that, for levels of disaggregation typical for real world IO data, the within-sector heterogeneity of carbon contents is very high in some industries. Exclusive use of aggregate IO data is not warranted, not even as starting value for iterative carbon accounting procedures. However, statistical data can be very useful in providing starting values for inputs from industries with low heterogeneity, such as many service industries, in cases where direct information is missing. They may also be used to approximate indirect emissions, when company level information on direct emissions is available. With the upcoming reporting requirements in place, this will be a standard case.

**Keywords:** greenhouse gas intensities, carbon accounting, green finance

**JEL classification:** Q56, Q51, C81

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# Harnessing the Power of Input-Output Analysis for Sustainability

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## 1 Introduction

Carbon contents are a key input for all sorts of allocation decisions, for consumers, investors and government agencies, and for the reliable identification of transition risks. Carbon content disclosures and estimations can come on various levels: national, sectoral, group and single company, installations and – without a time dimension – the product level. Quite generally, a major problem for estimating carbon contents are Scope 3 emissions: the carbon dioxide emitted for the production of intermediate inputs. Producers may know their inputs, but they still need good estimates of the carbon contents of these inputs unless there is direct information from providers. In trade policy, it is extremely important to reliably assess the carbon content of imports, in order to avoid carbon leakage.

Input-Output (IO) models provide the natural basis for organising the available information. On a sectoral basis, they take account of all production interlinkages – at least conceptually – using data that is available in most countries, often in a harmonised way. Combining the Input-Output matrix with sectoral information on direct emissions, one can readily track those emissions over the entire value chain up to the point of final use. Statisticians spend considerable resources to make this information available and to keep it up to date.

Within the new G 20 Data Gaps Initiative (DGI) framework,[2] Recommendation 1 on Greenhouse gas emission accounts and national carbon footprints asks countries and International Organisations for enhancing IO tables and emission statistics in such a way that consistent data is available for all major economies: regarding sector definitions, interlinkage information, information on import and export of intermediary inputs and direct emission statistics for sectors.

In order to contribute to this work stream, the project presented here looks for how aggregate measurement and IO tables can best be developed as an important source for firm level and product level estimates. The following issues need to be addressed:

- Sector level information in both emission statistics and IO need to be refined in business areas with high carbon intensity and with large heterogeneity. In both respects, energy, industrial production and agriculture stand out against service industries such as education, insurance and finance;
- IO sector definitions need to fit available data on carbon emissions and energy use, to make efficient use of existing information;

[2] See Ducharme (2022).

- It is important that sector definitions be geared to emerging mandatory disclosure rules for companies, as these rules comprise rankings against peer groups of companies, themselves defined on a sectoral level;
- Information on production interlinkages is to be combined with thorough information on international trade.

Specifically, I investigate the use of aggregate statistics for firm level and product level analysis for the case of the USA. The Bureau of Economic Analysis (BEA) works out extremely refined IO tables. Roughly every 5 years, benchmark statistics with no less than 405 industries and product groups are produced, in addition to the annual tables for 71 industries. In addition, the coverage of US companies in micro level databases on carbon emissions is generally much better than for any other nation. Information on trade interlinkages and emissions are available for a reduced set of sectors from OECD IO tables.

The rest of this paper is structured as follows. Section 2 describes the idea of setting up a simulation lab as a tool for designing and evaluating aggregate statistics. Section 3 shows how the data base is set up, using micro data from information providers and combining these with rather disaggregated industry level information on production interaction. This can be used to study the information content of more aggregated statistical information. The main challenge is to fit the micro level data into the structure of the existing information on interactions. Section 4 then introduces the relevant measurement concepts and the framework needed for computing carbon contents from data on direct emissions and production interactions. Section 5 gives a descriptive view of the data. The preliminary look has a focus on direct and indirect emissions and the resulting carbon contents. For many industries, companies are very heterogeneous in their direct emissions even at the lowest level of aggregation.

Ultimately, section 6 gives a first and as yet incomplete attempt to assess the predictive use of aggregate level statistical information for assessing the carbon content of output. I distinguish the direct use of industry level data as a predictor from the use in a unit level carbon accounting framework. The former means, for example, using industry level information for evaluating the carbon footprint of asset portfolios. The latter indicates the use of industry level information as a substitute of missing direct information on elements of the value chain. Given the high within-sector heterogeneity of carbon contents in some industries, the exclusive use of aggregate IO data is not warranted, not even as starting value for iterative carbon accounting procedures. On the other hand, statistical data can be useful in providing starting values for inputs from industries with low heterogeneity, such as many service industries, or with a low share in total input, when direct information is missing. Ideally, accountants have unit level information on the direct emissions of suppliers, e.g. from ESG reporting, and only need to fill up information gaps regarding indirect emissions.

## 2 A simulation lab

I start with micro level information on company emissions. Trucost Environmental Data has sectoral classifications for the companies that is closely related to the BEA sectoral divisions for Input Output tables. Both are based on the NAICS system of company classification. The micro database contains information on direct emissions and energy use, together with information on the sector and turnover. The data base consists of about 5000 units, almost exclusively from the United States and Canada. It allows a rather complete tracking of private economy value chains

Using sector level information matching what is available in the micro data, one can construct survey weights for units. With these weights, I can build a micro simulation of the US economy that reproduces the sectoral structure, the aggregate emissions and the known production interactions. To a much more limited degree, international linkages can be taken into account using the aggregated OECD IOCIO tables. To create firm specific variations, emissions, output and production interlinkages can be disturbed by white nose shocks. Micro level carbon contents are calculated using the methodology developed and explained in von Kalckreuth [2022a, 2022b].

This micro-simulation is **a laboratory to assess various questions of measurement** related to the DGI Recommendation mentioned above, specifically:

- How important are granular sectoral distinctions in areas of activity where emissions are heterogeneous and/or high?
- How important is an explicit account of international interlinkages?
- How well can sectoral data serve as proxies for the carbon content of company level output or products?
- How informative are they as inputs in carbon accounting?

Based on the knowledge of the simulated "truth", it is possible to compute the average error associated with any measurement method. This amounts to setting up an infrastructure that will enable us to discuss measurement issues consistently and on a quantitative basis.

## 3 Building the data base

The principal goal in setting up the data base is to reconstruct and simulate the value chains of production, making use of the detailed BEA Input Output Table with its 405 industries. To this end, it is important to find micro level representation for as many BEA 405 industries as possible. I start by working out a correspondence table between the Trucost classification and BEA 405. Both are based on NAICS. Not for all BEA 405 industries there are counterparts in the Trucost classification and vice versa. In cases where a BEA 405 industry has no counterpart in the Trucost data, I assign companies from closely related classes within the same BEA 71 grouping. Therefore, a given company may be used as representative for more than one BEA 405 class. Thus, for a suitable assignment, it is important to capture the structure and heterogeneity of direct emission intensities and the use of energy (Scope 2 emission intensities). The structure of production interactions will be borrowed from IO tables and will be different according to BEA 405 industry.

I concentrate on observations from 2020. If for a given company there is no observation for 2020, I take the latest observations from the period 2016 and after. The sectors are filled using companies from the United States and Canada. Only if there is no such company available, companies from other parts of the world are being used as sector representatives, with a preference for European firms. The resulting micro level database consist of 4,988 units, with the following regional representation:

**Table 1: Regional composition of simulation micro data base**

| Region | Freq. | Perc. | Cum. |
|---|---|---|---|
| Europe | 69 | 1.38 | 1.38 |
| Asia / Pacific | 68 | 1.36 | 2.75 |
| Africa / Middle East | 4 | 0.08 | 2.83 |
| USA and Canada | 4,846 | 97.15 | 99.98 |
| Latin America and Caribbean | 1 | 0.02 | 100.00 |
| **Total** | **4,988** | **100.00** | |

The data on direct emissions and Scope 2 emissions for the 4,988 units come from 3818 different companies. The data set has representatives units for 389 out of 405 detailed level industries and 67 out of 71 summary level industries. The micro data is on listed companies, thus it misses all government activity, private households, religious organisations and independent artists, writers and performers. Apart from this, the coverage is complete.

This information is linked to Input Output Accounts data from BEA[3]. First, I generate symmetric industry by industry direct requirement matrices from the Commodity by Industry direct requirement matrix and the Industry by Commodity transformation matrix[4]. For every industry, this matrix indicates the value of inputs from any other industry needed to generate one dollar's value of output. The last detailed level direct requirement matrix dates from 2012. This detailed level matrix is extrapolated to 2020 using summary level matrices for 2012 and 2020.[5] In a small number of cases, some adjustments were necessary to prevent the value added becoming too small.

The resulting input-output matrix is "blown up" to the micro level by randomly assigning to each company one representative from each sector from which it receives inputs. Two units in the same sector may thus be linked to companies with rather different carbon intensity. The resulting 4988 x 4988 interaction matrix is modified by making direct use of data on energy use. The micro data has information on Scope 2 (first tier) carbon intensity. Assuming that this type of indirect emission comes mostly from electricity, the Scope 2 data is converted to unit specific input coefficients for electricity, using the weighted average direct carbon intensity of electricity producers in the Trucost data.[6] For consistency reasons, I set up a notional electricity distribution agent that buys all electricity produced among the units in the

[3] See BEA Input Output Accounts Data, downloaded 17.03.2023 and before.
[4] See the note Mathematical Derivation of the Total Requirements Tables for Input-Output Analysis, BEA 2017
[5] A detailed level matrix for the year 2017 is about to be published by the BEA and will allow a better approximation.
[6] Again, manipulating the requirement coefficients makes adjustments necessary in some cases.

data base and sells it to the users of electricity. With this mechanism, the resulting Scope 2 emissions in the simulation are equal to the data provided by Trucost by definition.

# 4 Measurement concepts: indirect emissions and carbon content[7]

Carbon content is defined recursively: it is the sum of direct emissions attributed to a product and the carbon content of all inputs, covering indirect emissions. Indirect emissions are the result of direct emissions in a chain – or rather a fabric – of other production processes. Those production interlinkages are key for the consistent treatment of indirect emissions. IO analysis is designed for this type of interlinkages, and in fact it has been used in tackling the issue of attributing resource consumption to final output at the sectoral level since the 1970s.

## 4.1 An IO view

To fix ideas, consider the following. In production planning, every process is defined by a *bill of material* (BoM) that specifies all inputs, plus a *route sheet* that explains how to combine them. A complex production process may be decomposed into several stages. Consider the BoM of product *k*,

$$\mathbf{a}_k = \begin{pmatrix} a_{k1} & a_{k2} & \dots & a_{kK} \end{pmatrix}' ,$$

with $a_{ki}$ being the quantity of good *i* that enters the production process. There are entries for all input goods in the economy, most of them with a value of zero, of course. Let the amount of GHG emitted directly be given as $d_k$. Let scalar $c_i$ be the carbon content of good *i*, the quantity of GHG that is emitted in the production of one unit. List the carbon contents of all input goods in a vector as well:

$$\mathbf{c} = \begin{pmatrix} c_1 & c_2 & \dots & c_K \end{pmatrix}' .$$

The carbon content of product *k* is then given as the sum of direct and indirect emissions. Importantly, we do not add a definition for indirect emissions, but simply define them recursively as the carbon content of inputs:

$$c_k = d_k + \mathbf{c}'\mathbf{a}_k = d_k + \sum_i c_i a_{ki} \quad . \tag{1}$$

Indirect emissions are the direct emissions at earlier stages of the value chain. The equation is both perfectly general and encompassing. It relates to products and activities and – for a given time span – to enterprises and sectors as well.

As it stands, the equation is a definition. It helps us understand the problems associated with gathering and processing information. For actual computation, all the $c_i$ corresponding to the BoM of product *k* are required. If these are known, we can calculate the carbon content of product *k* in a straightforward way from direct emissions and the BoM. This is like computing the energy content of food: it is enough that producers know the composition of their product and the energy content of the ingredients. How can carbon contents of outputs be calculated in a world where not all inputs carbon contents are known? Product carbon contents are interdependent – the value for any product will depend on the value of all inputs.

[7] The content of this section is adapted from Section 2.2 in von Kalckreuth [2022a].

## 4.2 A reduced form for product carbon contents

If the relevant elements of **c** are unknown, we can use equation (1) recursively and try to compute the carbon content involved, going up the value chain from more complex intermediate inputs down to primary and primitive inputs. The structure is well known from linear production planning and IO analysis, pioneered by Wassily Leontief, and it was indeed the same author who first proposed using IO models for analysing pollution generation associated with inter-industry activity.[8] Conceptually, we can solve for the carbon content of all products simultaneously. Let

$$\mathbf{A} = \left(\mathbf{a}_1 \quad \mathbf{a}_2 \quad \ldots \quad \mathbf{a}_K\right)$$

be the matrix of the BoMs for all output goods, 1,…,*K*. With $\mathbf{d}$ being the column vector of the associated direct emissions, one may write:

$$\mathbf{c}' = \mathbf{d}' + \mathbf{c}'\mathbf{A}. \qquad (1)'$$

Reordering and postmultiplying the "Leontief inverse" $\left(\mathbf{I} - \mathbf{A}\right)^{-1}$ yields:

$$\mathbf{c}' = \mathbf{d}'\left(\mathbf{I} - \mathbf{A}\right)^{-1}. \qquad (2)$$

The carbon contents (product *k* and all the others) result from their own direct emissions and the direct emissions of all the intermediate goods used for their production by intermediation of a matrix derived from the BoM that reflects the interlinkages in production. If the coefficients in the carbon content equation refer to empirical production technologies actually being used to produce goods, 1, …, *K*, it can be taken for granted that the inverse exists and all its elements are non-negative.

As simple and beautiful as this relationship is, it is not possible to use it directly. Matrix $\mathbf{A}$ comprises the BoMs for all products in the economy, including those that have been imported, and if a certain input is produced using two different technologies, it should actually have two separate entries. Meanwhile, vector $\mathbf{d}$ collects the direct emissions that characterise all of these processes. Except for simple cases, this cannot be dealt with at the micro level. Von Kalckreuth [2022a] shows that this is not necessary. Producers do not have to be aware of all the stages of the value chain – they only need to know their own technology and the carbon contents of the inputs as provided by their immediate suppliers. Just as the price mechanism is able to process an enormous amount of information in a decentralised way, there are ways to make the coordinated exchange of information between producers do the rest of the work. With the E-Liability carbon accounting approach, Kaplan and Ramanna [2021a, 2021b] have suggested a process that enables the necessary information exchange. One question this paper tries to answer is where initial values for an encompassing system of carbon accounting may come from.

[8] Wassily Leontief was awarded the 1973 Nobel Prize for the development of IO analysis. Leontief [1986] covers much of his work. Leontief [1970] himself introduced pollution by augmenting the technology matrix to include a row of pollution generation coefficients, see Qayum [1994] for a consistent reformulation. The direct approach taken here, postulating a proportional relationship between output and pollution, was first advanced, on a sectoral basis, by Just [1974] and Folk and Hannon [1974]. The formulations are equivalent. For IO analysis in general, see Miller and Blair [2022], and specifically Chapter 10 for environmental IO analysis. Suh [2010] is a collection of extensions and applications in the field of industrial ecology.

## 5 A look at the data

At the time of writing this draft, the construction work for the data base is not yet finished. Specifically, the micro information have yet to be linked to aggregate data. However, it is very interesting to look at the heterogeneity on the micro level. Using relationship (2) on the micro data on direct emission intensities and the micro level requirement coefficients in the simulation universe, I calculate the "true" unit specific carbon contents, with the associated indirect emission intensities. The same could be achieved by using relationship (1)' iteratively. Table 2 gives some descriptive statistics: on sales and on direct emissions, indirect emissions and carbon contents – the latter three both weighted and unweighted.

To convey an idea of industry heterogeneity, Table 3 gives weighted means of direct emissions and carbon content (the sum of direct and indirect emissions) for three BEA 71 industries: 11CA 'Farms', 22 'Utilities' and 325 "Chemical products". The table renders the averages of direct emissions and carbon contents on the level of the BEA 71 aggregate and the BEA 405 industries. The averages are weighted by sales. These tables can by no means interpreted as valid statistical information. Indirect emissions are simulated, the assignment of suppliers to producers is random and in many of the BEA 405 cells there are not more than one or two units. However, they give an impression of the type of heterogeneity involved. The direct emission intensities in the various modes of running a farm are surprisingly diverse. It is interesting to see how in much of the chemical industry direct emissions are dominated by indirect emissions. The example of "utilities" as a compound of electricity, gas distribution and water / sewage shows how badly the coarser sectoral classification may be geared to the need of assessing emission intensities.

**Table 2: Descriptive statistics**

**a) Unweighted**

| Variable | Mean | Std dev | Min | Max |
|---|---|---|---|---|
| Sales (k USD) | 4,782.3 | 21,313.7 | 0.0 | 523,964.0 |
| Dir emission int. g/USD | 117.4 | 598.8 | 0.0 | 22,366.0 |
| Indir emission int, g/USD | 174.4 | 213.2 | 4.3 | 2,340.0 |
| Carbon content, g/USD | 291.8 | 679.1 | 5.0 | 23,590.4 |

**b) Weighted by sales**

| Variable | Mean | Std dev |
|---|---|---|
| Sales (k USD) | 99,754.8 | 132,451.8 |
| Dir emission int. g/USD | 107.3 | 477.2 |
| Indir emission int, g/USD | 156.6 | 200.3 |
| Carbon content, g/USD | 263.9 | 554.6 |

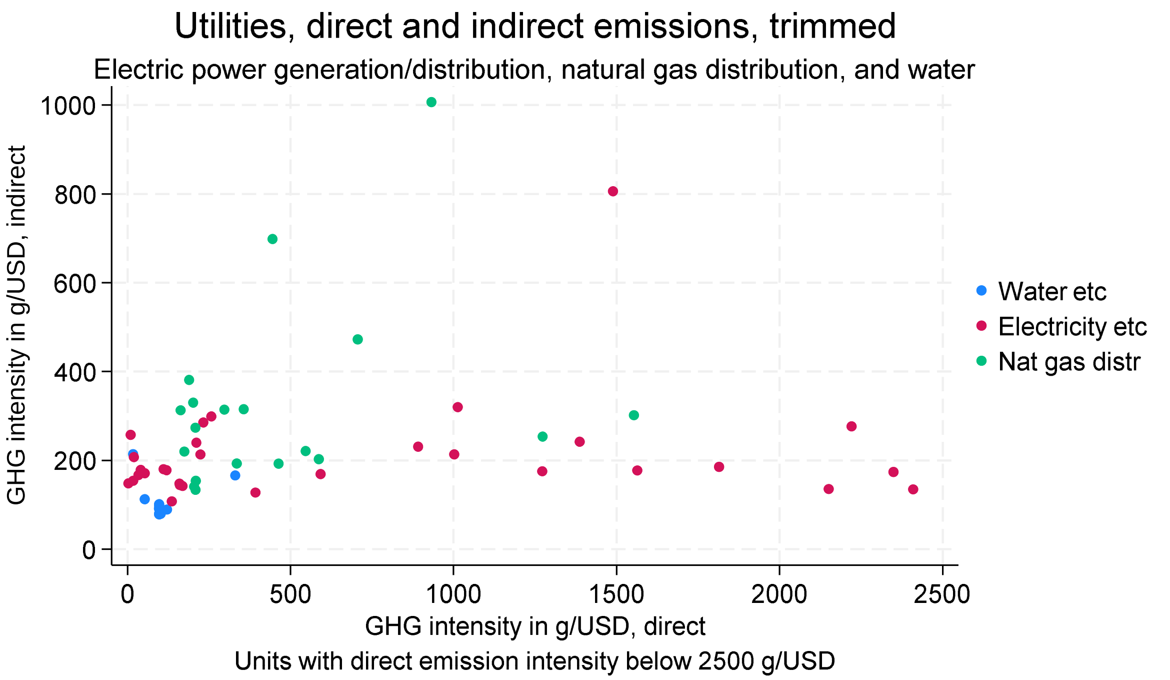
4,988 Observations on all variables

### Table 3: Weighted averages of direct emission intensities and carbon contents in three BEA 71 industries

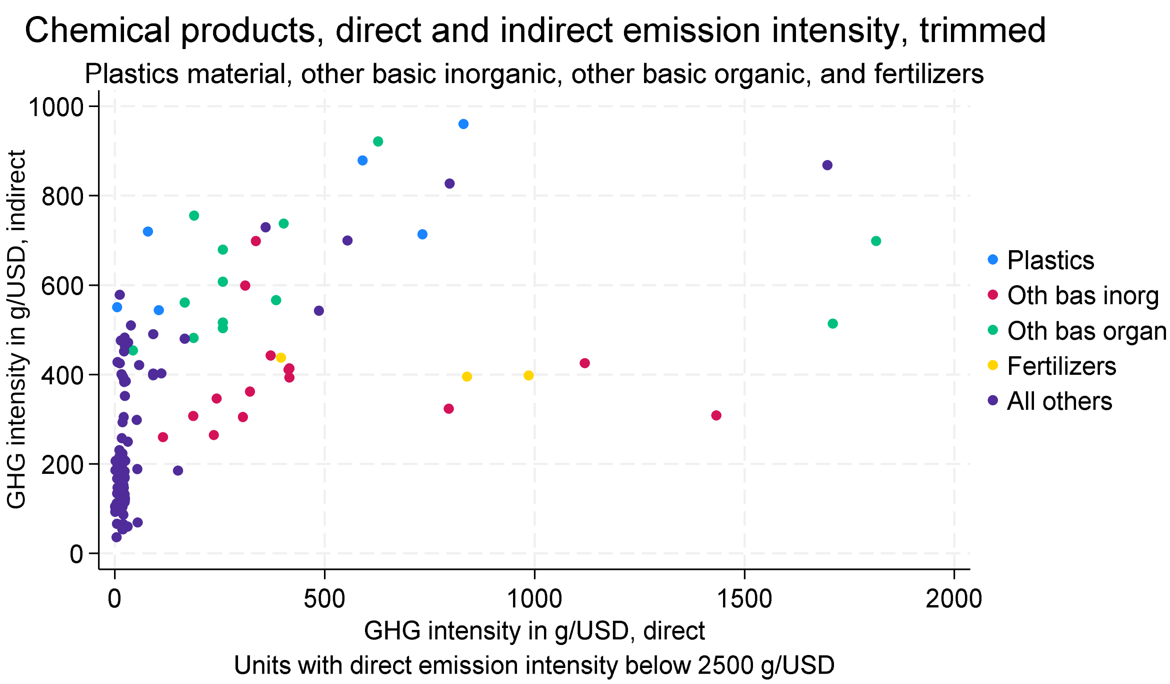
| BEA 71 industries | Emission intensities (g/USD) | |
|---|---|---|
| | direct em. | carbon content |
| **Farms** | | |
| **BEA 405 industries** | | |
| Oilseed farming | 1,604.2 | 1,938.2 |
| Grain farming | 1,096.6 | 2,020.3 |
| Vegetable and melon farming | 2,056.7 | 2,451.9 |
| Fruit and tree nut farming | 1,642.8 | 1,938.0 |
| Greenhouse, nursery, and floriculture production | 1,811.3 | 3,438.6 |
| Other crop farming | 578.4 | 1,037.6 |
| Dairy cattle and milk production | 662.5 | 1,491.4 |
| Beef cattle ranching and farming, including feedlots and dual purpose ranching and farming | 662.5 | 1,868.5 |
| Poultry and egg production | 1,715.3 | 2,786.7 |
| Animal production, except cattle and poultry and eggs | 1,040.2 | 1,304.1 |
| **Total** | **843.2** | **1,628.3** |
| **Utilities** | | |
| **BEA 405 industries** | | |
| Electric power generation, transmission, and distribution | 2,517.8 | 2,743.2 |
| Natural gas distribution | 809.5 | 1,230.6 |
| Water, sewage and other systems | 99.3 | 263.9 |
| **Total** | **2,216.4** | **2,470.3** |
| **Chemical products** | | |
| **BEA 405 industries** | | |
| Petrochemical manufacturing | 554.3 | 1,254.2 |
| Industrial gas manufacturing | 1,697.5 | 2,565.8 |
| Synthetic dye and pigment manufacturing | 797.7 | 1,625.0 |
| Other Basic Inorganic Chemical Manufacturing | 533.4 | 998.8 |
| Other basic organic chemical manufacturing | 670.2 | 1,350.8 |
| Plastics material and resin manufacturing | 653.3 | 1,411.9 |
| Synthetic rubber and artificial and synthetic fibers and filaments manufacturing | 407.8 | 1,065.9 |
| Medicinal and botanical manufacturing | 23.3 | 147.9 |
| Pharmaceutical preparation manufacturing | 17.0 | 150.5 |
| In-vitro diagnostic substance manufacturing | 20.5 | 161.8 |
| Biological product (except diagnostic) manufacturing | 9.4 | 65.7 |
| Fertilizer manufacturing | 1,595.3 | 2,035.5 |
| Pesticide and other agricultural chemical manufacturing | 74.9 | 455.1 |
| Paint and coating manufacturing | 19.3 | 487.2 |
| Adhesive manufacturing | 103.6 | 504.7 |
| Soap and cleaning compound manufacturing | 26.2 | 272.7 |
| Toilet preparation manufacturing | 6.5 | 212.4 |
| Printing ink manufacturing | 34.4 | 529.7 |
| All other chemical product and preparation manufacturing | 33.6 | 418.1 |
| **Total** | **168.2** | **450.8** |

To gain an insight into the variability on the micro level, we may first look at BEA 71 industry 22 ‘utilities’, with its three constituent BEA 405 industries: ‘Electric power generation, transmission, and distribution, ‘Natural gas distribution’, and ‘Water, sewage, and other systems’. Graph 1 is a scatterplot of direct emissions from individual level data and simulated indirect emissions for the utilities industry. It is obvious that knowledge of the detailed industry confers important information on the order of magnitude of direct and indirect emissions, but that there is important heterogeneity unaccounted for by detailed industry.

**Graph 1**




**Graph 2**




Graph 2 does a similar decomposition for the BEA 405 sector 325 ‘Chemical Products’. Table 1 shows the strong heterogeneity on the level of detailed industries, and Graph 2 gives an impression of the underlying micro level dispersion. Because of outliers, the scatter plot is trimmed at a value of 2500 g/$ for direct emission intensity. It is visible that the high intensity units are concentrated in a small number of BEA 405 industries.

This type of heterogeneity does not prevail everywhere. In large parts of the service sector, such as trade or where office work is predominating, direct and indirect intensities are low and uniform, the first mainly due to commuting and travel, the second to heating and electricity. Other services, such as transportation, are heterogeneous and in parts highly carbon intensive. Appendix 1 gives an overview of unweighted industry averages and standard deviations for direct emissions intensity and carbon contents according to BEA 71 industries. It readily appears that heterogeneity is enormous for some industries, while quite moderate for others.

# 6 Using industry level data for micro level predictions: first results

It is natural to attempt using industry averages as predictors or estimates for individual level outcomes. Actually, the European Commission is doing so on a large scale. The EU taxonomy for sustainable activities is simply a binary classification relying on industry as predictor. In the following, I will start by computing the Root Mean Squared Error (RMSE) of the weighted average using (1) the BEA 71, and (2) the BEA 405 industries as basis.[9] In both cases, only companies in BEA 405 industries with at least 3 units will be considered. The first is what can typically be achieved using statistical information based on the System of Environmental Economic Accounts (SEEA)[10]. Most regularly published national level IO Tables feature a similar number of industries. The second is, so to speak, the best possible sectoral predictor, at least for indirect intensities: in our idealised world, it is BEA 405 information that underlies the simulated production interlinkages.

**Table 4: Predictors for emission intensities – comparing RMSEs**

| Predictor | RMSE direct emission intensity | RMSE indirect emission intensity | RMSE total carbon content |
|---|---|---|---|
| BEA 71 weighted average | 339.7 | 100.7 | 362.4 |
| BEA 405 weighted average | 310.6 | 49.9 | 316.6 |
| Naïve carbon accounting, valuation of inputs using BEA 71 weighted average | - | 73.1 | 73.1 |
| Advanced carbon accounting, valuation of inputs using composite indicator | - | 21.0 | 21.0 |

Notes: RMSEs are roots of weighted mean squared prediction errors. They are calculated for units with an industry representation of 3 units at least. For carbon accounting estimators, RMSEs for direct emissions are zero by definition. The composite indicator for evaluating inputs in carbon accounting combines true direct emission intensities with weighted BEA 71 industry averages for indirect estimates.

In addition, I will consider predictors that use the rather coarse BEA 71 intensity information in combination with micro level information on input composition. These predictors, labelled "carbon accounting predictors", use correct unit level information on direct emissions and

[9] Strictly speaking, the sector level predictors need to be calculated on the basis of the Leontief inverses for industry aggregates, instead of averaging unit level results on the basis of a micro level Leontief matrix. Inverting a matrix is a non-linear operation, and due to the aggregation bias the results will not be identical. This will be completed at a later stage.

[10] The SEEA is a standard maintained by the United Nations, following similar accounting structures as the Standard of National Accounts (SNA), see System of Environmental Economic Accounting.

evaluate indirect emission intensity on the basis of equation (1), using BEA 71 industry averages as estimates of input carbon contents. This is the type of computation producers themselves can do: they know their own production routines well, but may not have first-hand information about the emission intensities of their suppliers. I distinguish two versions. A *naïve carbon accounting* solution uses industry averages of total carbon contents (direct and indirect) for the valuation of inputs. The *advanced carbon accounting* version takes one step further back: it evaluates inputs using a composite indicator as the sum of (true) direct emissions intensity of input providers and BEA 71 industry averages of indirect emissions intensity. That is, the producer is assumed to know their own direct emissions as well as the direct emission intensities of their supplier, relying on statistical information only for evaluating the indirect emissions of suppliers.

The results are collected in Table 4. The first two lines show the weighted Root Mean Squared Errors (RMSE) of predictors that directly use industry level data. For comparison: the overall weighted average of direct emissions is 107.31 g/$ compared to 156.56 g/$ for indirect emissions, see Table 1 above. The direct emission data are taken from the original data source. The high RMSE make clear that sectoral estimates for direct emission intensity are rather useless as predictors on the micro level, at least unconditionally. This is true for both the coarse BEA 71 average and the much more sophisticated BEA 405 average. Any use of industry level information on the level of micro entities will have to be selective.

The RMSE from the sectoral estimations are clearly smaller for indirect emissions than for direct emissions. This may reflect some amount of averaging, as indirect emissions come from many inputs. Furthermore, indirect emissions, reflecting the nature of the inputs, may indeed be stronger conditioned by industry than direct emissions. In addition, of course, the simulation might yet be missing important sources of variation for indirect emission.

For the two carbon accounting indicators, the errors for indirect emission intensities and total carbon content are identical by definition. The “naïve” carbon accounting estimate using the coarse BEA 71 information to evaluate inputs, combined with using adequate information on production technology, is right in the middle between the outcomes for the BEA 71 estimator and the sophisticated BEA 405 estimator. App. 2 shows the detailed industry level results.

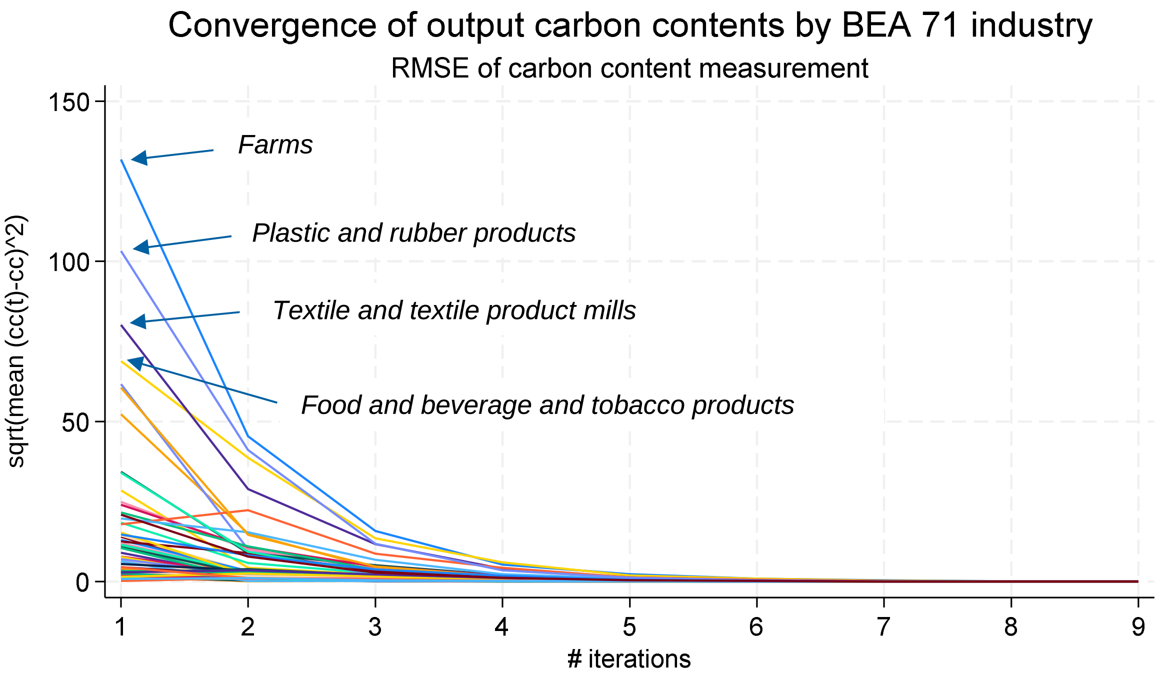
With the upcoming reporting requirements in the EU, there will often be exact and reliable information on Scope 1 and Scope 2 emissions on the company level. Useful information on Scope 3 emissions is much harder to obtain, as the relevant guidelines[11] leave many options, and data availability is a big concern for accountants. In those cases, industry level statistical information on indirect emissions may be a very useful complement for unit level information on direct emissions – much of the within-sector heterogeneity of carbon contents is due to the direct emissions component.

[11] For direct emissions and the use of energy, see the standards for disclosure of GHG Scope 1 and 2 emissions: WRI and WBCSD [2004]. For Scope 3 (indirect) emissions, see the two closely related standards for enterprise-level and product-level disclosure: WRI and WBCSD [2011a and 2011b]. Further, see the Technical Guidance for Calculating Scope 3 Emissions in WRI and WBCSD [2014].

For a composite indicator, the error dispersion for indirect emission intensity and overall carbon contents are equal by definition. Using it as valuation vector for inputs will bring down the RMSE of carbon accounting down to 21.0. This is the advanced carbon accounting indicator Again, App. 2 shows the details by industry. In most cases, RMSEs for carbon accounting using a composite indicator are very low. For some industries, however, using industry level information to guide the evaluation of inputs are clearly insufficient. This is specifically true for farms, food and beverages, the chemical industry and some other manufacturing industries.

Carbon accounting by definition uses the right composition of inputs – valuations will deviate from true values if the associated input carbon contents are wide off the mark. It has been shown formally that utilizing the carbon account evaluations of firms as an *input for the next stage of estimations* will make the estimates converge to the true values, see von Kalckreuth (2022a). To investigate this process and to show the rather heterogeneous outcomes from taking statistical aggregates as initial value of carbon accounting, I simulate the social learning process that consists in using carbon accounting methods iteratively. All industries are initiated by their weighted average carbon content, not the much more precise composite indicator.

**Graph 3**




The results are shown in Graph 3, for the case of starting out with advanced carbon accounting, i.e. initiating the process using the combined indicator. App. 2 shows the numerical values for errors for both types of initial values. Speed of convergence is rather high for most industries, but not for all. It becomes visible that for some sectors, RMSEs are high at the beginning and quite some way into the future, others are well aligned from the beginning. It appears that aggregate carbon contents can well be used as initial values for some sectors, but not for others. Obviously, using more precise (direct) information for industries with large heterogeneity will improve measurement for all industries, not just the industries affected. The graph for an adjustment process starting with naïve carbon accounting looks similar, starting from a much higher level, see App. 2.

Summarising these preliminary results, it appears that using industry averages of carbon contents directly as proxies for micro level outcomes is not warranted, except in industries with little heterogeneity, such as service industries with a strong focus on office work. Given the heterogeneity in BEA 405 industries, refining sector distinctions will not change this result in an overall sense, though further evaluation work is likely to show that it can be helpful for certain industries. This is an interesting outcome, given attempts by regulators to identify certain types of activity as either sustainable or non-sustainable. On the other hand, industry averages are useful building blocks in micro level computations, to make up for missing information on the value chain. In this respect, much is gained if unit level information on the direct emissions of input providers can be used, and statistical information is needed only to fill information gaps on indirect emissions.

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## Appendix 1: Descriptive statistics by BEA 71 industry

Unweighted statistics: Revenue, direct and indirect emissions, carbon content

| | | Rev | Dir em (kg/k$) | | Indir em (kg/k$) | | | Carbon content (kg(k$) | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **BEA 71 industry** | **#** | **Mean** | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** | **Min** | **Max** |
| Farms | 22 | 368 | 1086 | 775 | 802 | 428 | 1888 | 801 | 834 | 3546 |
| Forestry, fishing, and related a | 7 | 756 | 78 | 53 | 106 | 46 | 184 | 24 | 151 | 212 |
| Oil and gas extraction | 92 | 1643 | 966 | 1192 | 451 | 152 | 1417 | 1241 | 407 | 9978 |
| Mining, except oil and gas | 88 | 1206 | 507 | 985 | 431 | 156 | 938 | 1081 | 276 | 7550 |
| Support activities for mining | 39 | 1527 | 112 | 247 | 132 | 13 | 243 | 246 | 132 | 1662 |
| Utilities | 87 | 5193 | 1748 | 2168 | 245 | 212 | 1993 | 2188 | 151 | 10607 |
| Construction | 94 | 3564 | 79 | 337 | 195 | 65 | 274 | 352 | 118 | 2601 |
| Wood products | 17 | 2263 | 169 | 264 | 277 | 86 | 446 | 250 | 236 | 1363 |
| Nonmetallic mineral products | 29 | 1283 | 361 | 594 | 365 | 146 | 726 | 679 | 238 | 3833 |
| Primary metals | 39 | 3595 | 748 | 1159 | 750 | 255 | 1499 | 1235 | 449 | 6104 |
| Fabricated metal products | 65 | 1977 | 39 | 37 | 684 | 481 | 723 | 484 | 300 | 2376 |
| Machinery | 108 | 3744 | 16 | 11 | 327 | 104 | 343 | 104 | 162 | 745 |
| Computer and electronic products | 210 | 4698 | 27 | 39 | 58 | 34 | 85 | 62 | 18 | 595 |
| Electrical equipment, appliances | 47 | 1882 | 62 | 219 | 340 | 141 | 402 | 240 | 168 | 1695 |
| Motor vehicles, bodies and trail | 234 | 4645 | 13 | 9 | 531 | 243 | 545 | 243 | 280 | 1829 |
| Other transportation equipment | 37 | 8374 | 21 | 9 | 218 | 123 | 238 | 122 | 121 | 528 |
| Furniture and related products | 26 | 1790 | 16 | 5 | 389 | 190 | 405 | 189 | 214 | 1016 |
| Miscellaneous manufacturing | 95 | 2424 | 18 | 29 | 194 | 71 | 213 | 86 | 126 | 806 |
| Food and beverage and tobacco pr | 80 | 6675 | 58 | 73 | 641 | 286 | 699 | 311 | 164 | 1906 |
| Textile mills and textile produc | 13 | 1271 | 139 | 55 | 423 | 165 | 562 | 177 | 342 | 1016 |
| Apparel and leather and allied p | 13 | 2807 | 35 | 30 | 257 | 37 | 292 | 53 | 237 | 405 |
| Paper products | 17 | 5630 | 699 | 1512 | 475 | 76 | 1175 | 1499 | 457 | 6961 |
| Printing and related support act | 3 | 1622 | 25 | 5 | 205 | 37 | 230 | 41 | 183 | 256 |
| Petroleum and coal products | 24 | 23816 | 576 | 706 | 673 | 150 | 1250 | 748 | 638 | 3815 |
| Chemical products | 213 | 4099 | 246 | 1576 | 250 | 216 | 496 | 1677 | 40 | 23590 |
| Plastics and rubber products | 26 | 2471 | 61 | 61 | 492 | 138 | 554 | 143 | 331 | 872 |
| Wholesale trade | 176 | 14368 | 29 | 71 | 80 | 21 | 109 | 86 | 30 | 839 |
| Motor vehicle and parts dealers | 20 | 7946 | 27 | 7 | 99 | 9 | 126 | 15 | 81 | 140 |
| Food and beverage stores | 20 | 24837 | 11 | 5 | 107 | 19 | 118 | 21 | 75 | 152 |
| General merchandise stores | 11 | 32009 | 9 | 4 | 119 | 16 | 128 | 19 | 97 | 157 |
| Other retail | 139 | 15260 | 13 | 18 | 112 | 21 | 125 | 29 | 63 | 312 |
| Air transportation | 21 | 4056 | 1243 | 604 | 127 | 33 | 1370 | 609 | 766 | 3763 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Rail transportation | 5 | 11192 | 447 | 71 | 191 | 29 | 638 | 57 | 569 | 720 |
| Water transportation | 13 | 1316 | 1508 | 832 | 144 | 26 | 1653 | 831 | 504 | 3234 |
| Truck transportation | 20 | 2492 | 162 | 93 | 149 | 19 | 311 | 96 | 242 | 657 |
| Transit and ground passenger tra | 2 | 6752 | 0 | 0 | 66 | 7 | 66 | 6 | 61 | 70 |
| Pipeline transportation | 16 | 6036 | 860 | 670 | 149 | 114 | 1009 | 672 | 181 | 2508 |
| Other transportation and support | 17 | 12888 | 64 | 77 | 140 | 17 | 204 | 76 | 102 | 365 |
| Warehousing and storage | 3 | 1749 | 60 | 49 | 217 | 99 | 277 | 141 | 134 | 416 |
| Publishing industries, except in | 162 | 2105 | 4 | 1 | 26 | 7 | 30 | 7 | 18 | 63 |
| Motion picture and sound recordi | 15 | 975 | 3 | 2 | 74 | 13 | 77 | 15 | 40 | 110 |
| Broadcasting and telecommunicati | 118 | 14439 | 5 | 4 | 78 | 26 | 83 | 28 | 37 | 187 |
| Data processing, internet publis | 114 | 4314 | 3 | 1 | 78 | 31 | 82 | 32 | 40 | 402 |
| Federal Reserve banks, credit in | 404 | 1720 | 1 | 0 | 31 | 6 | 32 | 6 | 24 | 73 |
| Securities, commodity contracts, | 178 | 6573 | 23 | 213 | 53 | 13 | 76 | 215 | 35 | 2097 |
| Insurance carriers and related a | 186 | 18079 | 3 | 25 | 35 | 7 | 38 | 28 | 23 | 307 |
| Funds, trusts, and other financi | 37 | 1867 | 0 | 0 | 71 | 75 | 71 | 75 | 53 | 517 |
| Housing | 414 | 991 | 21 | 35 | 79 | 69 | 99 | 79 | 5 | 822 |
| Other real estate | 207 | 991 | 21 | 35 | 178 | 55 | 199 | 67 | 104 | 720 |
| Rental and leasing services and | 139 | 729 | 22 | 94 | 74 | 51 | 96 | 116 | 32 | 989 |
| Legal services | 1 | 5984 | 1 . | | 43 . | | 44 . | | 44 | 44 |
| Computer systems design and rela | 78 | 3393 | 8 | 4 | 34 | 18 | 42 | 19 | 15 | 114 |
| Miscellaneous professional, scie | 335 | 1059 | 15 | 56 | 82 | 17 | 97 | 63 | 41 | 1180 |
| Management of companies and ente | 1 | 62 | 7 . | | 66 . | | 73 . | | 73 | 73 |
| Administrative and support servi | 46 | 2667 | 11 | 26 | 86 | 48 | 97 | 68 | 34 | 460 |
| Waste management and remediation | 9 | 4072 | 542 | 484 | 199 | 40 | 741 | 490 | 290 | 1454 |
| Educational services | 21 | 1138 | 18 | 5 | 126 | 43 | 144 | 46 | 70 | 217 |
| Ambulatory health care services | 124 | 7999 | 18 | 4 | 87 | 27 | 105 | 28 | 62 | 194 |
| Hospitals | 13 | 8228 | 17 | 2 | 99 | 4 | 115 | 4 | 108 | 122 |
| Nursing and residential care fac | 18 | 1391 | 18 | 1 | 126 | 10 | 144 | 10 | 127 | 158 |
| Social assistance | 3 | 1515 | 18 | 0 | 144 | 55 | 162 | 55 | 127 | 225 |
| Performing arts, spectator sport | 8 | 1080 | 9 | 0 | 74 | 8 | 83 | 8 | 68 | 91 |
| Amusements, gambling, and recrea | 22 | 395 | 9 | 2 | 130 | 53 | 139 | 53 | 67 | 238 |
| Accommodation | 28 | 1328 | 49 | 84 | 200 | 195 | 249 | 277 | 110 | 1579 |
| Food services and drinking place | 99 | 2433 | 22 | 8 | 160 | 23 | 182 | 26 | 123 | 285 |
| Other services, except governmen | 18 | 1739 | 21 | 4 | 93 | 28 | 114 | 30 | 67 | 166 |
| Federal government enterprises | 2 | 7311 | 26 | 10 | 83 | 1 | 109 | 9 | 103 | 116 |
| **Total** | **4988** | **4782** | **117** | **599** | **174** | **213** | **292** | **679** | **5** | **23590** |

## Appendix 2: Carbon contents and RMSEs for three estimators by BEA 71 industry

Weighted statistics: RMSEs 1) of BEA 71 averages, composite indicator and carbon accounting

| BEA 71 industry | # | Mean carbon content Weighted | RMSE BEA 71 averages Weighted | RMSE composite indicator (initial value) Weighted 2) | RMSE carbon accounting indicator, 1st iteration Weighted 3) |
|---|---|---|---|---|---|
| Farms | 22 | 1628.3 | 563.5 | 379.3 | 131.8 |
| Forestry, fishing, and related a | 7 | 190.6 | 20.2 | 33.7 | 4.6 |
| Oil and gas extraction | 92 | 1278.8 | 587.8 | 104.7 | 11.2 |
| Mining, except oil and gas | 88 | 906.6 | 922.3 | 186.0 | 28.6 |
| Support activities for mining | 39 | 242.9 | 180.2 | 17.3 | 9.1 |
| Utilities | 87 | 2470.3 | 2051.7 | 171.5 | 11.7 |
| Construction | 94 | 194.4 | 84.7 | 61.4 | 4.3 |
| Wood products | 17 | 494.1 | 311.3 | 77.6 | 14.0 |
| Nonmetallic mineral products | 29 | 969.8 | 676.4 | 139.9 | 18.4 |
| Primary metals | 39 | 1635.0 | 1332.0 | 216.4 | 52.3 |
| Fabricated metal products | 65 | 716.2 | 356.7 | 343.9 | 61.7 |
| Machinery | 108 | 334.7 | 84.3 | 82.2 | 14.4 |
| Computer and electronic products | 210 | 61.2 | 71.9 | 39.4 | 1.6 |
| Electrical equipment, appliances | 47 | 390.1 | 189.6 | 134.0 | 24.9 |
| Motor vehicles, bodies and trail | 234 | 512.9 | 231.0 | 230.4 | 34.3 |
| Other transportation equipment | 37 | 171.6 | 82.8 | 81.6 | 13.1 |
| Furniture and related products | 26 | 368.5 | 163.1 | 164.9 | 24.0 |
| Miscellaneous manufacturing | 95 | 193.5 | 55.8 | 55.2 | 21.6 |
| Food and beverage and tobacco pr | 80 | 726.3 | 365.6 | 340.1 | 68.8 |
| Textile mills and textile produc | 13 | 623.6 | 142.6 | 118.3 | 80.1 |
| Apparel and leather and allied p | 13 | 270.7 | 36.5 | 24.9 | 17.9 |
| Paper products | 17 | 827.6 | 566.3 | 65.2 | 19.7 |
| Printing and related support act | 3 | 230.8 | 31.9 | 29.5 | 12.5 |
| Petroleum and coal products | 24 | 1184.2 | 321.0 | 122.7 | 34.0 |
| Chemical products | 213 | 450.8 | 623.8 | 223.2 | 60.5 |
| Plastics and rubber products | 26 | 586.4 | 132.0 | 112.7 | 103.2 |
| Wholesale trade | 176 | 101.2 | 77.6 | 20.5 | 3.8 |
| Motor vehicle and parts dealers | 20 | 123.6 | 16.4 | 9.3 | 2.5 |
| Food and beverage stores | 20 | 106.5 | 27.9 | 22.4 | 12.0 |
| General merchandise stores | 11 | 117.8 | 8.7 | 8.1 | 10.7 |
| Other retail | 139 | 110.2 | 19.9 | 15.9 | 3.6 |
| Air transportation | 21 | 1298.3 | 340.4 | 44.4 | 7.8 |

| | | | | | |
|---|---|---|---|---|---|
| Rail transportation | 5 | 630.4 | 42.0 | 24.9 | 10.5 |
| Water transportation | 13 | 1260.3 | 517.9 | 26.2 | 7.8 |
| Truck transportation | 20 | 333.5 | 112.1 | 23.0 | 4.2 |
| Transit and ground passenger tra | 2 | 68.8 . | . | . | |
| Pipeline transportation | 16 | 1022.0 | 534.9 | 104.7 | 2.0 |
| Other transportation and support | 17 | 292.5 | 84.0 | 12.5 | 4.2 |
| Warehousing and storage | 3 | 248.6 | 134.6 | 93.3 | 11.5 |
| Publishing industries, except in | 162 | 38.3 | 10.1 | 10.6 | 1.4 |
| Motion picture and sound recordi | 15 | 65.1 | 19.9 | 18.8 | 1.6 |
| Broadcasting and telecommunicati | 118 | 101.1 | 26.0 | 25.3 | 6.9 |
| Data processing, internet publis | 114 | 91.8 | 37.1 | 36.8 | 2.2 |
| Federal Reserve banks, credit in | 404 | 35.4 | 4.7 | 4.4 | 1.2 |
| Securities, commodity contracts, | 178 | 95.2 | 290.7 | 10.8 | 1.7 |
| Insurance carriers and related a | 186 | 72.2 | 94.8 | 9.9 | 3.0 |
| Funds, trusts, and other financi | 37 | 62.1 | 43.6 | 43.6 | 3.6 |
| Housing | 414 | 86.8 | 97.8 | 94.1 | 2.4 |
| Other real estate | 207 | 184.5 | 80.0 | 75.5 | 15.4 |
| Rental and leasing services and | 139 | 177.4 | 256.5 | 75.9 | 1.7 |
| Legal services | 1 | 43.8 . | . | . | |
| Computer systems design and rela | 78 | 58.7 | 27.2 | 28.0 | 6.4 |
| Miscellaneous professional, scie | 335 | 80.9 | 37.9 | 22.4 | 4.4 |
| Management of companies and en | 1 | 73.4 . | . | . | |
| Administrative and support servi | 46 | 85.0 | 53.9 | 42.9 | 4.1 |
| Waste management and remediati | 9 | 1180.4 | 363.2 | 34.6 | 7.0 |
| Educational services | 21 | 162.3 | 46.6 | 43.6 | 3.2 |
| Ambulatory health care services | 124 | 84.0 | 24.6 | 23.6 | 5.5 |
| Hospitals | 13 | 115.2 | 2.4 | 2.4 | 1.7 |
| Nursing and residential care fac | 18 | 145.1 | 8.8 | 9.3 | 2.9 |
| Social assistance | 3 | 161.9 | 44.8 | 44.8 | 14.7 |
| Performing arts, spectator sport | 8 | 80.2 | 7.3 | 7.4 | 1.9 |
| Amusements, gambling, and recrea | 22 | 141.5 | 55.4 | 55.3 | 3.3 |
| Accommodation | 28 | 303.8 | 330.4 | 232.2 | 1.6 |
| Food services and drinking place | 99 | 169.5 | 39.1 | 31.5 | 3.0 |
| Other services, except governmen | 18 | 92.5 | 30.9 | 26.7 | 4.6 |
| Federal government enterprises | 2 | 114.8 . | . | . | |
| **Total 4)** | **4988** | **291.8** | **172.7** | **77.3** | **13.2** |

**Notes:**

1) RMSEs only computed for cells with 3 observations or more
2) true direct emissions, indirect emissions estimated as averages over BEA 71 industries
3) Values resulting from one iteration of carbon accounting: true direct costs, true input compositions, valuation of inputs using averages
4) Total for RMSEs is weighted means of sectoral RMSEs, not the RMSE for the total sample