Econometric estimates of the Danish CO_2 emission multipliers on the basis of supply-use tables: performance of emission reductions via external trade

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Abstract

Climate Change is currently on the mainstream of the economic science and particularly, environmental input-output analysis is increasingly playing a relevant role in measuring economic and environmental effects of sustainable development policies in Europe. Nevertheless, other approaches co-exist, such as the econometric modelling, where impacts are quantified on statistical grounds and with certain desirable properties (efficient estimates, confidence intervals, hypothesis testing, *etc*) that are not found in the input-output approach. Therefore, this paper merges both approaches to address the calculation of unbiased and consistent carbon dioxide emission multipliers for Denmark and their respective confidence intervals. The use of the supply and use system instead of the symmetric input-output table also brings in the chance to avoid usual problems in the construction of technical coefficients (technology assumptions, negatives, *etc*). Moreover, a new application of these multipliers with policy relevance is introduced to quantify the performance of the carbon dioxide emission reductions carried out by industries via external trade.

Keywords: carbon dioxide emissions; air emissions; climate change; supply and use tables; input-output analysis.

Note: The views expressed in this paper belong to the authors and should not be attributed to the European Commission or its services.

1 Background

Carbon dioxide (CO_2) emissions are considered to be one of the main sources of climate change. Consequently, there are currently worldwide major efforts being carried out by governments to reduce the amount of CO_2 emissions. But certainly, the problem really arises when we want to identify which are the most pollutant activities or at least, which are the most environmentally harmful products consumed by final users. Yet, the environmental impact of final consumption was expressed by Leontief (1970) as an undesirable externality of the production process (by-product). Then, it might happen that final users from one developed country will be demanding emission intensive products to other developing country via external trade. Apparently, the former country would emit less but at the cost of a likely increase in emissions made by the developing country just to satisfy this new demand. Eventually, the global outcome might well be an increase in emissions rather than a reduction. Hence, the decomposition of total emissions into domestic and embodied emissions in imports turns out to be of extreme relevance in the current global policy agenda in order to elucidate environmental responsibilities at the country level. Moreover, the emissions considered should take into account not only direct emissions but those indirectly emitted by supplier industries to produce a certain commodity.

The paper is structured as follows: the next section presents briefly the current methodological framework under which input-output economists and industrial ecologists account for environmental impacts and, particularly, carbon dioxide emission multipliers. It also provides some clues on stochastic input-output modelling and the construction of input-output tables from a supply-use system, all of which will be integrated into a single modelling framework. Section 3 introduces an econometric model that provides domestic and total unbiased and consistent emission multipliers. Sections 4 and 5 show an application for Denmark both on theoretical and empirical grounds and the last section concludes with a summary of the most prominent findings.

2 Methodological framework

2.1 Input-output economics and industrial ecology

Following Suh and Kagawa (2005), recent developments have situated Life Cycle Assessment (LCA), a key subfield of industrial ecology, as one of the areas that most extensively use input-output analysis (IOA). LCA can be considered a tool that allows quantifying and evaluating the environmental impacts of a product over the course of its entire life-cycle (Guinée et al, 2002). Presently, IOA is an important part of LCA practice and both methods and data for IO and LCA models are under rapid development (see Joshi, 1999; Matthews and Small, 2001; Suh and Huppes, 2002; Lenzen et al, 2004). Another area where IOA is deeply linked to industrial ecology is the product policy field. The European Commission adopted a Communication (EC, 2003) that identifies products with the greatest potential for environmental improvement as a basis for implementing the European Integrated Product Policy and recognized IO-LCA as one of the approaches well suited for IPP analyses (see Suh and Kagawa, 2005; Weidema *et al.* 2004; Tukker *et al.* 2005). The rapid generalization and evolution of systems such as Systems of Environmental and Economic Accounts (SEEA) and National Accounting Matrices including Environmental Accounts (NAMEA) (see, for instance, Haan and Keuning, 1996; EC, 2001; UN, 2003) is also providing an international accounting framework where input-output tables are supplemented by an increasing number of natural resource accounts (land, water, forestry…) and environmental emissions at industry level. With this purpose, among others, there are currently two EU funded projects (EXIOPOL[1] and WIOD[2]) that envisage the completion of big databases of supply-use tables and input-output tables including environmental accounts at the global level. Indeed, IOA is also rapidly broadening its scope of application to industrial ecology on the extension of the analysis to a global level. For instance, the World Trade Model developed by Duchin (2005) and extended in Stromman *et al.* (2005) has been used to examine the global implications of the changes in agricultural land yields to due to future climate change. (Juliá and Duchin, 2005).

To our knowledge, the IO type of analysis used so far by LCA practitioners is based almost exclusively on the Leontief quantity model (Dietzenbacher, 1995) and the multipliers obtained through the so called Leontief inverse. By changing the quantities consumed of products by final users, the Leontief quantity model yields variations in industry outputs (considering industry by industry IO tables). Therefore, under certain emission coefficients per unit of industry output provided generally by LCA practitioners and/or NAMEA accounts, we could determine the change in the emissions occurred as a result of the initial variation in final demand.

Emission multipliers have been reported in a number of studies. Proops *et al.* (1993) made a comparative study of the German and British case, while Östblom (1998) addressed the environmental outcome of emission intensive economic growth in the Swedish economy. Lenzen (1998) used an input–output model to investigate the energy and greenhouse gas flows within the Australian economy; Gerilla *et al.* (2001) studied the environmental repercussions of changes in technology in the Japanese economy; De Haan (2001) developed a structural decomposition analysis of pollution in the Netherlands; Creedy and Sleeman (2005) addressed emission reductions in New Zealand; and Lenzen *et al.* (2004) developed a multi-regional model to compute emission multipliers and emission balances.

Several applications to the Spanish carbon dioxide emissions are also worthwhile to mention: Alcántara and Roca (1995) used the input–output model to analyse the primary energy requirements and carbon dioxide emissions during the period 1980–1990. Cadarso and Fernández-Bolaño (2002) and Serrano and Roca (2007) reviewed the influence of the patterns of growth and consumption on the environmental pollution in Spain. Butnar *et al.* (2006) used a generalized input–output model which determined the key sectors and the input paths of air pollution through the decomposition of global multipliers with structural path analysis. Llop (2007) decomposes total changes in emission multipliers to account for changes in emission coefficients (polluting intensity) and changes in technical coefficients (economic structure). Finally, Rodríguez Morilla *et al.* (2007) computed the emission multipliers of greenhouse effect gasses using Social Accounting Matrix and Environmental Accounts (SAMEA).

[1] www.feem-project.net/exiopol/
[2] www.wiod.org

2.2 Stochastic input-output analysis

So far so good. However, there has been to our knowledge very little attention paid by IO-LCA practitioners to the positive and significant biasedness of the multipliers derived from the Leontief inverse (see Dietzenbacher, 2006). By assuming a stochastic technical coefficients matrix A, a central result is that the Leontief inverse is positively biased (see Simonovits, 1975; Lahiri, 1983; and Flam and Thorlund-Petersen, 1985). In line with Dietzenbacher (2006), we argue that the overestimation of the multipliers is not a negligible issue at all. Because the Leontief inverse is usually post-multiplied by an exogenously specified (positive) final demand vector, all the separate positive biases cumulate in the projection for the output levels, for instance. Needless to say, the emission impacts calculated from biased output levels generate even more biased estimation of emission multipliers.

Dietzenbacher (2006) also discusses what kind of initial stochastic table is more plausible from an economic point of view. In deriving analytical results, it seems more convenient to assume stochastics on the input coefficients under some mathematical assumptions. However, input coefficients are derived from symmetric input-output tables (IOTs) and these should therefore be taken as a starting point instead. Although more plausible from an economic viewpoint, this has rarely been adopted (see Gerking, 1976, 1979; and Dietzenbacher, 1988). The probable reason is that the additional step of transforming intermediate uses into input coefficients seriously complicates the analysis, typically inducing a rather complex stochastic nature of the input coefficients.

However, it was not until ten Raa and Rueda-Cantuche (2007) when the stochastic nature was assumed neither on the input coefficients nor on the elements of the IOT (or transactions table) but rather on the supply and use (firms) data used to compile the official supply and use tables, which incidentally forms the previous step to construct an IOT. These authors proposed a single-equation econometric model in which the regression coefficients result in the equivalent output multipliers obtained through the Leontief inverse and under the product technology assumption for the construction of the input coefficients matrix A. The authors estimated output and employment multipliers and compared them to the ones obtained through the Leontief inverse. The results confirmed the positive bias on almost all of the significant multipliers. One main advantage of this approach is that we are able to estimate unbiased and consistent multipliers to be applied further on to the calculation of emission changes due to variations in final demand quantities. Moreover, we can determine confidence intervals at certain significance levels and make standard hypotheses tests on the individual significance of the multipliers or on the model as a whole. However, this approach is limited heavily by the data availability at the firm level.

2.3 Supply, use and input-output tables

Another relevant issue in the calculation of the input coefficients is the technology assumption to be used for the compilation of the IOT, if this is product by product (see for a review, ten Raa and Rueda-Cantuche, 2003). The same applies for industry by industry IOTs between two alternative delivery assumptions (Eurostat, 2008). There is abundant literature and a longstanding controversy on the best method to compile IOTs on theoretical grounds. On the one hand, Kop Jansen and ten Raa (1990) proved that the product technology assumption *i.e.* all products are produced in the same way irrespective of the producer industry) is the best method to compile product by product tables, whilst on the other hand, Rueda-Cantuche and ten Raa (2008) proved recently that for industry by industry tables, the horse winner is the fixed industry sales structure assumption *i.e.* constant deliveries of industries irrespective of the products they sell. Anyway, the direct use of supply-use tables and not the input matrix *A* would fully prevent us from addressing this controversy of the IO literature.

2.4 Contributions

So, how this paper may contribute to the IO-LCA community? This paper merges for the very first time (to our knowledge) the use of econometric modelling tools within a supply-use system to address environmental repercussions (carbon dioxide emissions) from changes in quantities consumed by final users (see Figure 1). This approach provides in one shot unbiased and consistent estimates of emission (carbon dioxide) multipliers on the basis of official supply and use tables (note that this differs slightly from the approach based on firm's data). It also provides confidence intervals for emission multipliers. Under this approach, no longer a Leontief inverse is needed to compute total emission impacts. Only with published supply-use tables (both at basic prices[3]), data on direct emission coefficients and some standard econometrics, IO-LCA practitioners can estimate statistically significant impacts. This paper shows an application for Denmark and discusses its current performance on emission (carbon dioxide) reductions by importing emission intensive products from other countries.

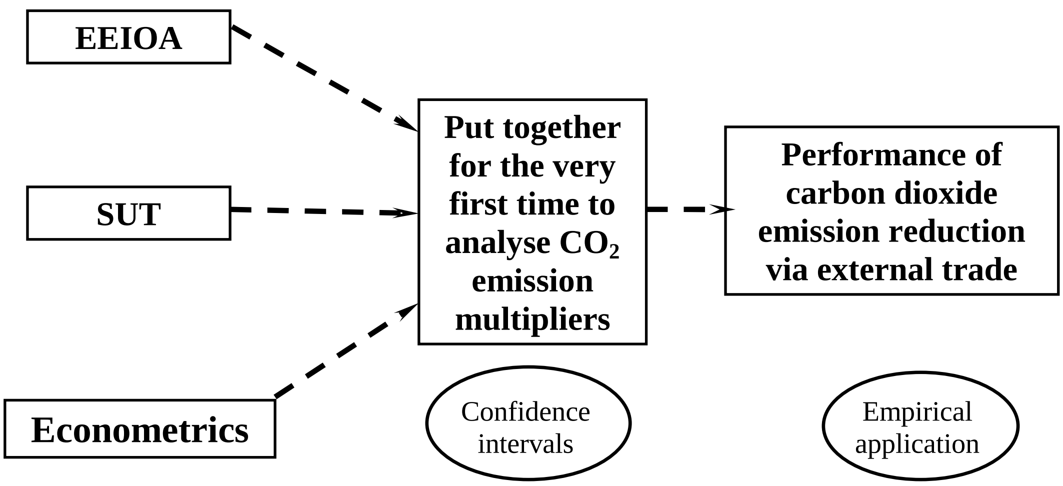

Figure 1: Scheme of the process followed in the paper.

Following ten Raa and Rueda-Cantuche (2007), the practice of interrelating accounts and input-output multipliers can be decomposed into three steps, see Figure 2.

[3] The basic price concept consists of purchasers' prices minus distribution margins and net taxes on products.

Step 1 consists of filling data gaps, imputing values to non-observed establishments, and summation over firms within industries. These operations are straightforward and produce the so-called use and make tables U and V (being the latter the transposed production matrix of a supply table), which display the commodity inputs and outputs of the industries. The off-diagonal elements of the make table are the so-called secondary products, which must be treated one way or another in Step 2. The result is a matrix of input-output coefficients, A. The third and last step is Leontief inversion, $(I - A)^{-1} = I + A + A^2 + \ldots$. In multiplier analysis, the first term represents the direct effect, the second term the direct input requirement, and the third and further terms the indirect input requirements.

The literature is as piecemeal as Figure 2 suggests. The theory of input-output coefficients addresses Step 2 and analyzes alternative models for their construction. Results are partial and problems persist, such as the problem of negative coefficients. The stochastic input-output literature focuses on Step 3, analyzing the transmission of errors under Leontief inversion. Here the problem is also nonlinearity, but not one associated with the presence of secondary products. As stated before, multipliers with positive bias are expected.

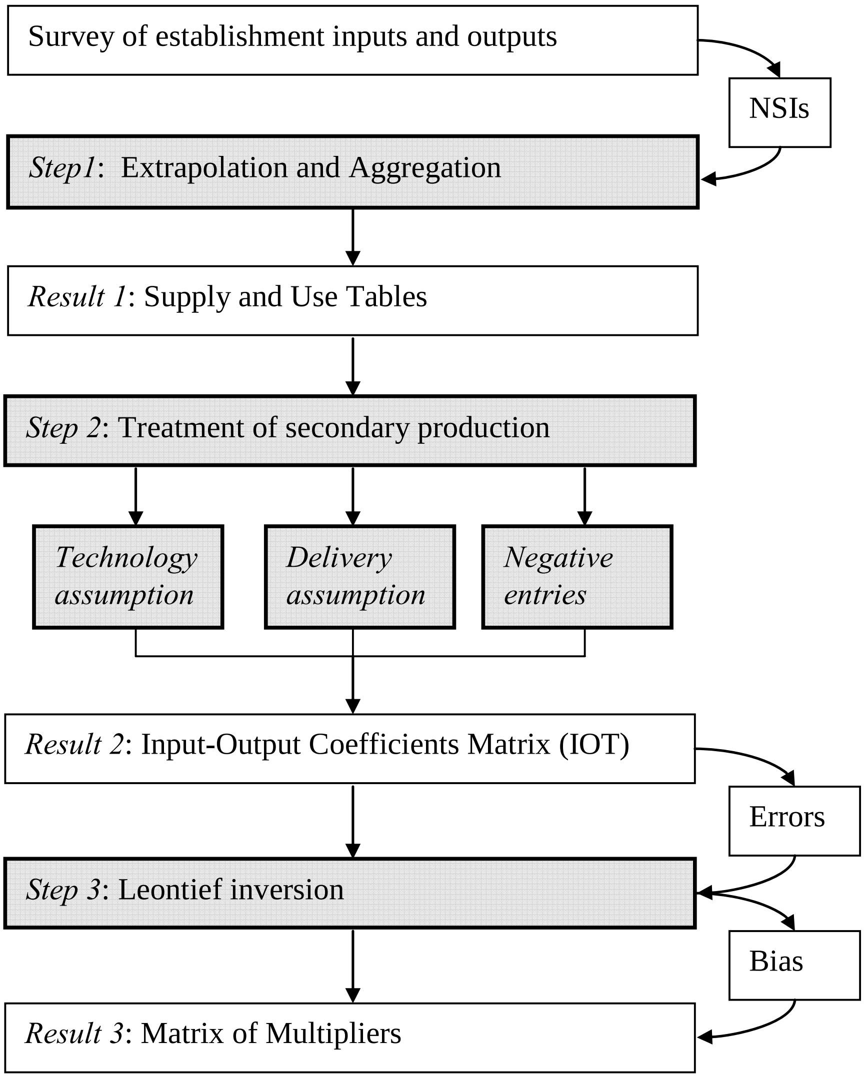

Figure 2: From establishment data to input-output multipliers

In this paper we make two interrelated contributions to the literature. First, we derive information on the precision of multipliers not from stochastic assumptions on the input-output coefficients, but from the variability of the make-use statistics across industries (note that this differs slightly from ten Raa and Rueda-Cantuche (2007) who placed stochastic assumptions directly on firms input and output data). In other words, we go back just only to square 3 instead of 1 in Figure 1 for the sake of simplicity and data availability. Second, we integrate the steps of Figure 1, by reducing the formulas for multipliers to the use and make tables. To our delight, the nonlinearities, which plague the construction of input-output coefficients and the transmission of errors in the Leontief inverse, neutralize each other. In this way we are able to present consistent linear unbiased estimates of multipliers. We contrast our results with the official ones of the Statistics Denmark (2007) for the year 2003.

3 Econometric computation of carbon dioxide emissions multipliers

As in Miller and Blair (1985) and following ten Raa (2005) and ten Raa and Rueda-Cantuche (2007), among others, a row vector of carbon dioxide emission multipliers (γ) is denoted by the following expression:

$$\gamma = c(I - A)^{-1} \tag{1}$$

where c stands for a row vector of carbon dioxide (direct) emission coefficients and $(I\text{-}A)^{-1}$ for the usual Leontief inverse. Each value of γ measures the total (direct and indirect) emissions produced as a result of one-unit increase in the quantities consumed by final users for a certain commodity. Next, by assuming the product technology assumption in the sense that carbon dioxide direct emission levels of a commodity are independent of the producing industry, we denote:

$$\begin{aligned} C &= cV^{T} \\ c &= CV^{-T} \end{aligned} \tag{2}$$

being C a row vector of industry carbon dioxide direct emission levels; and V^T (transposed of the intermediate matrix of a make table) a production matrix of the supply table at basic prices (product by industry).

Similarly, the construction of the input matrix A under the product technology assumption is given by:

$$\begin{aligned} U &= AV^{T} \\ A &= UV^{-T} \end{aligned} \tag{3}$$

where A represents the matrix of technical coefficients (product by product) and U, the intermediate part of a use table at basic prices (product by industry. Bearing in mind the two former assumptions, equation (1) becomes into:

$$\gamma = CV^{-T}\left(I - UV^{-T}\right)^{-1} = C\left[\left(I - UV^{-T}\right)V^{T}\right]^{-1} = C\left(V^{T} - U\right)^{-1} \tag{4}$$

which can be expressed as:

$$C = \gamma(V^T - U) \quad \textbf{(5)}$$

For the same number of industries than products, equation (5) would not be anything else than a system of equations with one single solution for the γ coefficients. But however, rectangular systems typically derived from make and use tables usually have different numbers of industries and of products, and thus allowing for the introduction of a random disturbance error ε, which will defined as a row vector of m independent and normally distributed errors with zero mean and constant variance. That is:

$$C = \gamma(V^T - U) + \varepsilon \quad \textbf{(6)}$$

Then, emission multipliers become a vector of regression coefficients, γ. In (6), C is a m-order row vector (m industries) of carbon dioxide direct emissions; γ corresponds to a n-order row vector (n products) of emission multipliers; V is the make matrix of order m x n, and U is the use matrix of order n x m (products by industry).

It must be noted that, as far as m is the number of industries, it is also the number of observations and that direct emissions by commodities would therefore constitute the independent variables of the resulting model, n. Note that, since our approach uses published supply and use tables instead of firms' data as in ten Raa and Rueda-Cantuche (2007), we had to aggregate products in order to get enough degrees of freedom (m-n) for the model. Obviously, more industries than products (m>n) are required. As long as we fulfil this requirement and have enough degree of freedom then the equations system (5) is over-determined and the regression model is computable.

4 Assessing the performance of emission reductions via external trade

Firstly, let us denote Y as a final demand matrix depicting final use of products supplied by industries (rows) to different categories (consumption, government, capital and exports). This can be split into domestic and imported final uses: Y_m and Y_d.

Secondly, the sum of domestic supply plus imports makes the total supply (at basic prices). However, a supply table only provides a full matrix for the domestic side. Therefore, we had to distribute the column vector of imports row-wise in proportion to the row structures of the domestic supply table. This implies that the industry supplier structure of the products imported resembles that of the domestic supply. Then, we denote V_d as the domestic supply matrix and V_m as the import supply matrix. The sum of the two should make V.

And thirdly, total intermediate uses (U) of a use table at basic prices can be decomposed also into domestic (U_d) and imported uses (U_m). The above definitions can be expressed then mathematically as follows:

$$Y = Y_d + Y_m \quad \textbf{(7)}$$

$$V = V_d + V_m \quad \textbf{(8)}$$

$$U = U_d + U_m \quad \textbf{(9)}$$

Furthermore, from the National Accounts System (EC, 1995 and UN, 1993), we may write the following identities (at basic prices).

$$V_d^T e = Y_d e + U_d e \quad \textbf{(10)}$$

$$V_m^T e = Y_m e + U_m e \quad \textbf{(11)}$$

where e represents a unitary vector of suitable dimensions. Indeed, the sum of domestic intermediate uses of products plus the corresponding domestic final uses makes the total domestic supply. The same applies for imports.

Now, summing (10) and (11), on both sides of the equations, it is verified that total intermediate uses plus total final demand matches total supply at basic prices. That is:

$$V_d^T e + V_m^T e = U_d e + U_m e + Y_d e + Y_m e \quad \textbf{(12)}$$

Finally, it is easy to understand that considering equations (1), (6), (8) and (9), we may postulate the Leontief quantity model for total (domestic and import) uses like:

$$\gamma_t = c(I - A_t)^{-1} \quad \textbf{(13)}$$

$$C + C_m = \gamma_t (V_d^T + V_m^T - U_d - U_m) + v \quad \textbf{(14)}$$

where $_t$ stands for "total" in the sense of (12). So γ_t would represent a row vector of emission multipliers that would include direct and indirect emissions occurred due to a variation in the final demand of domestic and foreign products. C_m represents carbon dioxide emissions embodied in imports. A central issue is the availability of data about C_m, which is seldom. In order to circumvent this problem, Leontief (1953) already proposed a few decades ago to use the domestic technology assumption for capital and labour production intensities (Leontief paradox). In the same line, Statistics Denmark (2007) provides data on C_m using the same assumption as Leontief did.

In other words, γ_t can be considered as a measure of the maximum polluting capacity (per one-unit increase of final demand quantities) of an economy in the sense that if all imported products were produced domestically, that would yield to the maximum levels of emissions that the current domestic technology would emit. But in the real outside world countries indeed import and the emissions are transferred abroad via external trade. Now, if we only consider domestic supply and uses, from a national perspective, then C_m=0 (this does not mean that there are not emissions but they are produced abroad and not domestically). As a result, equations (13) and (14) can be rewritten respectively as:

$$\gamma_d = c(I - A_d)^{-1} \quad \textbf{(15)}$$

$$C = \gamma_d (V_d^T - U_d) + \varepsilon \quad \textbf{(16)}$$

where $_d$ stands for "domestic", in the sense of (10). Hence, γ_d yields a row vector of emission multipliers computed taking into account only domestically produced inputs and outputs.

Bearing in mind that γ_d is expected to be benchmarked by γ_t since we have used the same domestic technology for the production of both domestic and foreign products; we propose the following ratio to quantify the performance of the emission reduction efforts of a country via external trade and differentiated by industries. The *ratio of performance, R,* would be as follows:

$$R = 1 - \frac{\gamma_d}{\gamma_t} \quad \textbf{(17)}$$

In this sense, *R* gives an idea of how far is the current productive structure of an economy from the maximum emission levels per unit of output that can be achieved (R=1) with the current domestic technology. For example, let γ_d be equal to 5 tonnes and γ_t be equal to 10 tonnes (*R*=1/2=0.5) for a certain product, then the Danish imports of such commodities allow Denmark to be at the 50% of its maximum polluting capacity per unit of output. Evidently, as long as the *R* value is closer to 1, then the corresponding industry is benefitting from the external trade to reduce its emissions. The contrary applies to values of R close to 0.

5 Data and results

The empirical work was carried out for the Danish economy using official supply and use tables (SUTs) for the year 2003 (59 industries/commodities) valued at basic prices and expressed in millions of Danish Krone at current prices. We had to aggregate up to 21 pollutant-wise groups of commodities in order to have enough number of degrees of freedom (59 industries – 21 commodities = 38 degrees of freedom) to estimate equations (14) and (16).

The model has been estimated by means of ordinary least squares. Due to the presence of certain forms of unknown heteroskedasticity, the White estimate (White, 1980) of the covariance matrices of estimated coefficients was used to provide consistent and robust standard errors. We do not find problems of autocorrelation (as expected in cross-sectional data) and multicollinearity do not plague our analysis. Only 1 out of the 210 (0.48%) possible off-diagonal elements of the correlations matrix with 21 different explanatory variables (for both models) was larger than 0.5, and none greater than 0.75.

For comparison purposes, the Leontief inverse based emission multipliers were not constructed on the basis of the official A_{59x59} matrix published by the Danish Statistics Office, but on a pure product technology basis for our aggregated 21 sectors/products, input matrix A_{21x21}. This means that equation (1) was computed using an aggregated version of published SUT_{59x59} and the product technology model, as expressed in equation (3).

Finally, Statistics Denmark (2007) published NAMEA Accounts for 2003. Hence, we used published data on the direct carbon dioxide emissions coming both from the use of domestic and foreign products. Statistics Denmark used the domestic technology assumption to estimate the emissions generated by foreign products demanded by Danish final users (Statistics Denmark, 2007). This publication presents data on industry emissions with a breakdown of 130 industries that had to be aggregated to 59. Table 1 shows the sectors that directly emit most to the environment in Denmark. In Table 1, the emissions generated abroad by foreign products imported to Denmark are not included.

Code	Commodity	Domestic direct emissions (CO_2 tonnes)	Domestic direct emissions (percentage)
01	Products of agriculture, hunting and related services	2,283	4.0%
02	Fish and other fishing products; services incidental of fishing	614	1.1%
03	Coal, uranium and other mining and quarrying products	305	0.5%
04	Crude petroleum & natural gas; and incidental related services	2,071	3.7%
05	Food products and beverages; Tobacco	1,644	2.9%
06	Textiles, leather, wood, cork, pulp, paper and paper products	628	1.1%
07	Coke, refined petroleum products and nuclear fuels	1,014	1.8%
08	Chemicals, rubber and plastics	717	1.3%
09	Other non-metallic mineral products	3,214	5.7%
10	Metallurgy and fabricated metal products	390	0.7%
11	Machinery and equipment; electrical machinery & apparatus	318	0.6%
12	Office mach. & computers; radio, TV & communication equip. medical & precision intruments; transport equip.	136	0.2%
13	Furniture; other manufactured goods; secondary raw materials	248	0.4%
14	Electricity, gas, steam and hot water	34,202	60.4%
15	Construction work	1,270	2.2%
16	Trade; hotel and restaurant services	1,256	2.2%
17	Land transport	2,236	3.9%
18	Water transport	742	1.3%
19	Air transport	1,666	2.9%
20	Other services	949	1.7%
21	Public Admin. Education and Health & social work services	758	1.3%

Source: Statistics Denmark (2005)

Table 1: Domestic direct emissions in Denmark (2003)

Electricity, gas, steam and hot water generation (14) amounts a bit more than 60% of the total emissions while the other non-metallic mineral products (5.7%), products of agriculture, hunting and related services (4%), land transport (3.9%) and crude petroleum and natural gas (3.7%) make 17.3%. In terms of direct emission coefficients (tonnes per million of Danish Krone), they provide a different ranking (see Table 2) for all sectors except for electricity (14), which has the greatest value (1,107.4 tonnes per million of Danish Krone); and other non-metallic mineral products (09), with the second biggest emission coefficient (191.3 tonnes). Next, the fishing industry (171.8 tonnes), the coal, uranium and other mining and quarrying products (129 tonnes) and the air transport complete the top-five list. Moreover, when considering direct and indirect emissions either through the econometric model and/or the Leontief inverse based calculations, the top-five list remains unchanged although with a slight exchange of ranking positions between coal mining and the fishing industry, in the case of the econometric estimation.

Code	Commodity	Emission Coefficient	Emission multipliers: Leontief calculation	Emission multipliers: Econometric. Calculation: Multipliers	p value	CI bounds: lower	CI bounds: upper	estimated bias
		(CO_2 tonnes *per* million of Danish Krone)						
01	Products of agriculture, hunting and related services	33.5	67.6	62.2	0.000	60.9	63.5	-5.4
02	Fish and other fishing products; services incidental of fishing	171.8	200.6 #	190.2	0.000	175.5	204.9	-10.4
03	Coal, uranium and other mining and quarrying products	129.0	164.3	232.4	0.000	212.1	252.7	68.1
04	Crude petroleum and natural gas; and incidental related services	50.0	52.9	59.7	0.000	58.9	60.6	6.9
05	Food products and beverages; Tobacco	13.6	60.8	22.7	0.000	22.2	23.2	-38.1
06	Textiles, leather, wood, cork, pulp, paper and paper products	9.9	37.4	19.1	0.000	9.7	28.4	-18.3
07	Coke, refined petroleum products and nuclear fuels	42.8	104.6	114.7	0.000	113.1	116.3	10.1
08	Chemicals, rubber and plastics	10.0	36.2	20.3	0.000	19.7	20.9	-15.9
09	Other non-metallic mineral products	191.3	248.5	240.9	0.000	237.6	244.2	-7.6
10	Metallurgy and fabricated metal products	9.1	32.0 #	30.6	0.000	29.1	32.1	-1.4
11	Machinery and equipment; electrical machinery & apparatus	3.7	20.7	12.4	0.000	11.6	13.1	-8.4
12	Office mach. & computers; radio, TV & communication equip. medical & precision intruments; transport equip.	2.7	15.7	4.6	0.005	1.5	7.8	-11.1
13	Furniture; other manufactured goods; secondary raw materials	10.4	35.4	11.4	0.000	8.3	14.6	-24.0
14	Electricity energy, gas, steam and hot water	1107.4	1,124.0	1,218.0	0.000	1,198.8	1,237.3	94.0
15	Construction work	8.2	35.1	24.0	0.000	22.1	25.8	-11.1
16	Trade; hotel and restaurant services	4.3	24.1	15.6	0.000	14.5	16.6	-8.6
17	Land transport	39.0	56.1 #	57.2	0.000	55.8	58.7	1.1
18	Water transport	7.0	10.8	9.4	0.000	8.8	10.1	-1.3
19	Air transport	109.8	126.7	116.9	0.000	111.5	122.2	-9.8
20	Other services	1.5	13.5 #	15.4	0.002	5.9	25.0	2.0
21	Public Admin. Education and Health & social work services	2.1	14.0	3.0	0.004	1.0	4.9	-11.0

Key: p value = 0.000: p values lower than 10^{-4} are rounded, but different from null. #: Within the CI bounds

CI bounds: Confidence Intervals bounds at a confidence level of 95%.

Note: All the coefficients are significant at the 99% confidence level.

Table 2: Carbon dioxide emission multipliers

Table 2 also shows to what extent a sector has a large emission multiplier due to the extensive use of intermediate pollutant inputs. We could have such an overview by relating the direct emission coefficients to the econometric multipliers (direct and indirect). These sectors are typically: other services (20); trade, hotel and restaurant services (16); metallurgy and fabricated metal products (10); machinery and equipment (11); construction work (15) and coke and refining products (07), among others.

From Table 2, we have derived additionally the following considerations on the basis of a comparison between the carbon dioxide emission multipliers obtained from the econometric model and those derived from the Leontief inverse.

a) In most cases, the Leontief inverse based multipliers overestimate the unbiased values given by the econometric regression. Indeed, 15 out of 21 (71.4%) commodities have lower estimated multipliers than those calculated with the traditional approach. Confirming the results reported by Dietzenbacher (2006), the magnitude of the estimated bias tends to be small and positive. The weighted[4] average of the positive estimated biases only amounts 2.1% while that of the negative biases yields -0.1%. Similar results were provided by Dietzenbacher (1995), Roland-Holst (1989) and ten Raa and Rueda-Cantuche (2007).
b) Econometric input–output (ordinary least squares) estimates are unbiased and consistent, providing confidence intervals for carbon dioxide emissions multipliers. These intervals measure the accuracy of the estimates. Notice that only four multipliers derived from the traditional approach fell within the confidence intervals.
c) The measurement of the extent to what sectors use extensively intermediate pollutant inputs is also affected by the bias. Since the Leontief inverse based multipliers are generally overestimated, then it may appear that sectors like office machinery (12) consumes emission-intensive inputs not being really the case when using the econometric multipliers. The same applies to furniture and other manufactured goods (13) and public administration, education and health and social work services (21).

In order to test significant correlations between the different rankings obtained from the econometric and Leontief based approaches, respectively, we compute the Spearman coefficient of correlation, which amounted 0.91, being also significant with a 99% confidence level. The same applies to the Pearson correlation coefficient, which amounts to 0.967.

Table 3 presents the results of the estimated equations (14) and (16) together with the results of the ratio of performance (R) given by (17). As expected, domestic emission multipliers are always lower than total emission multipliers. Figure 3 shows that the most eco-efficient sectors in transmitting emissions abroad via external trade are: water transport (18); office machinery and computers (12); machinery and equipment (11); food products (05) and chemicals, rubber and plastics (08). To the contrary, coal mining (03) and fishing activities (02) reported the lowest values indicating inefficient reduction of emissions through external trade. To a less extent, air transport (19); electricity, gas, steam and hot water (14); and the extraction of crude petroleum and natural gas (including incidental related services) (04) did not perform well either.

[4] The weights used are the shares of the econometric estimates of emission multipliers.

Code	Commodity	Domestic model				Total model				*R*
		Multiplier	CI bounds		p value	Multiplier	CI bounds		p value	
			lower	upper			lower	upper		
01	Products of agriculture, hunting and related services	62.2	60.9	63.5	0.000	204.6	176.8	232.4	0.000	0.70
02	Fish and other fishing products; services incidental of fishing	190.2	175.5	204.9	0.000	238.5	132.3	344.7	0.000	0.20
03	Coal, uranium and other mining and quarrying products	232.4	212.1	252.7	0.000	281.5	-34.8	597.9	0.079	0.17
04	Crude petroleum & natural gas; and incidental related services	59.7	58.9	60.6	0.000	141.0	124.2	157.8	0.000	0.58
05	Food products and beverages; Tobacco	22.7	22.2	23.2	0.000	178.1	163.2	193.1	0.000	0.87
06	Textiles, leather, wood, cork, pulp, paper and paper products	19.1	9.7	28.4	0.000	98.5	41.2	155.8	0.001	0.81
07	Coke, refined petroleum products and nuclear fuels	114.7	113.1	116.3	0.000	318.0	285.5	350.5	0.000	0.64
08	Chemicals, rubber and plastics	20.3	19.7	20.9	0.000	151.6	123.7	179.4	0.000	0.87
09	Other non-metallic mineral products	240.9	237.6	244.2	0.000	549.6	500.0	599.2	0.000	0.56
10	Metallurgy and fabricated metal products	30.6	29.1	32.1	0.000	95.1	72.2	118.0	0.000	0.68
11	Machinery and equipment; electrical machinery & apparatus	12.4	11.6	13.1	0.000	108.8	86.6	131.0	0.000	0.89
12	Office mach. & computers; radio, TV & communication equip. medical & precision intruments; transport equip.	4.6	1.5	7.8	0.005	65.8	21.8	109.8	0.005	0.93
13	Furniture; other manufactured goods; secondary raw materials	11.4	8.3	14.6	0.000	84.6	21.7	147.5	0.010	0.86
14	Electrical energy, gas, steam and hot water	1,218.0	1,198.8	1,237.3	0.000	2,742.3	2,687.2	2,797.3	0.000	0.56
15	Construction work	24.0	22.1	25.8	0.000	108.8	92.1	125.4	0.000	0.78
16	Trade; hotel and restaurant services	15.6	14.5	16.6	0.000	57.3	40.7	74.0	0.000	0.73
17	Land transport	57.2	55.8	58.7	0.000	191.8	175.2	208.4	0.000	0.70
18	Water transport	9.4	8.8	10.1	0.000	418.1	416.4	419.8	0.000	0.98
19	Air transport	116.9	111.5	122.2	0.000	219.7	161.1	278.4	0.000	0.47
20	Other services	15.4	5.9	25.0	0.002	58.9	11.8	106.0	0.016	0.74
21	Public Admin. Education and Health & social work services	3.0	1.0	4.9	0.004	14.7	7.4	22.0	0.000	0.80

Key: p value = 0.000: p values lower than 10^{-4} that are been rounded, but different from null.

CI bounds: Confidence Intervals bounds at a confidence level of 95%.

Table 3: Domestic and total carbon dioxide emission multipliers

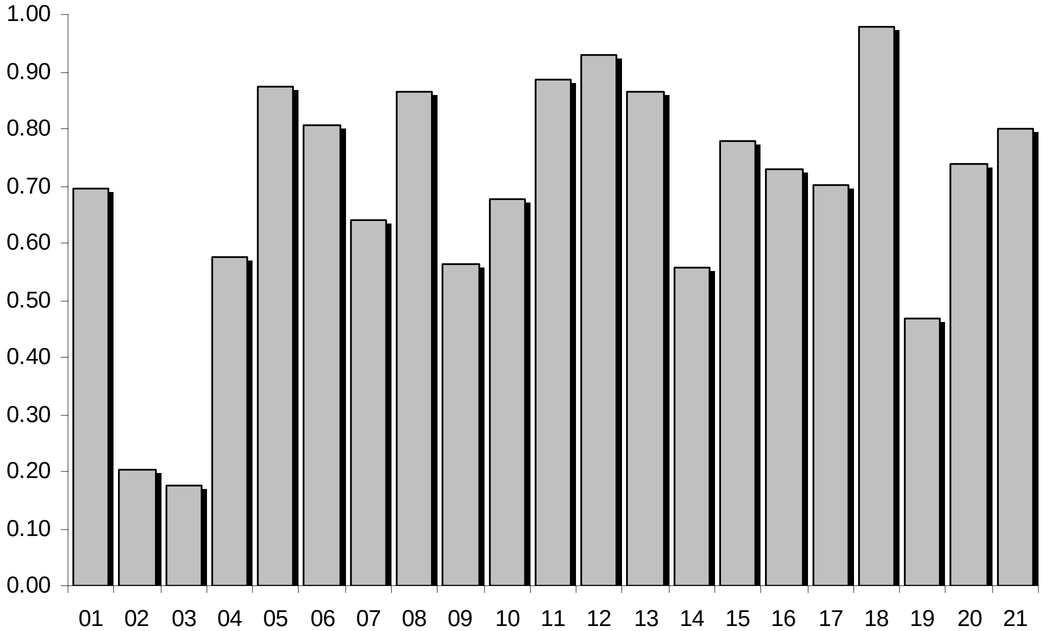

Figure 3: Ratio of performance

It may be of interest to note that it is expected that the larger the share of imports, the larger the ratio of performance (with a maximum of 1). That would mean that external trade is indeed influencing in the reduction of emissions of sectors like: water transport (18); office machinery (12); machinery and equipment (11); and textiles (06). Other sectors like coal mining (03) and crude petroleum and natural gas (04) have small shares of imports and therefore, small values for R. However, we can find specific industries with a large share of imported primary products but with low values of R or, in other words, not performing very well in the transfer of emissions abroad via external trade (*e.g.* refining petroleum products (07) and air transport (19)). On the contrary, other services (20) have small shares of imported services but they are enough to keep them far away from its maximum capacity to pollute. At this respect, it is useful to bear in mind that domestic emission multipliers may vary according to different import shares and that the elasticity between them plays an important role (see Figure 4).

Figure 4 represents the way import shares and emission multipliers may be related. When all imports are produced domestically (s = 0 and R = 0) then, total emission multipliers match domestic emission multipliers. On the contrary, if everything is imported then the domestic emission multiplier is zero (R = 1). Let us assume a certain share of imports (s_o) with γ_d associated domestic emission multiplier. Then, if we assume an increase in the share of domestically produced goods and services (reduction of import shares), then this would lead to raise emissions up to γ_A, γ_B or γ_C, depending on the selected straight line: A, B or C, respectively (see Figure 4). Model C can be considered inelastic in comparison to model A while model B is more elastic than model A.

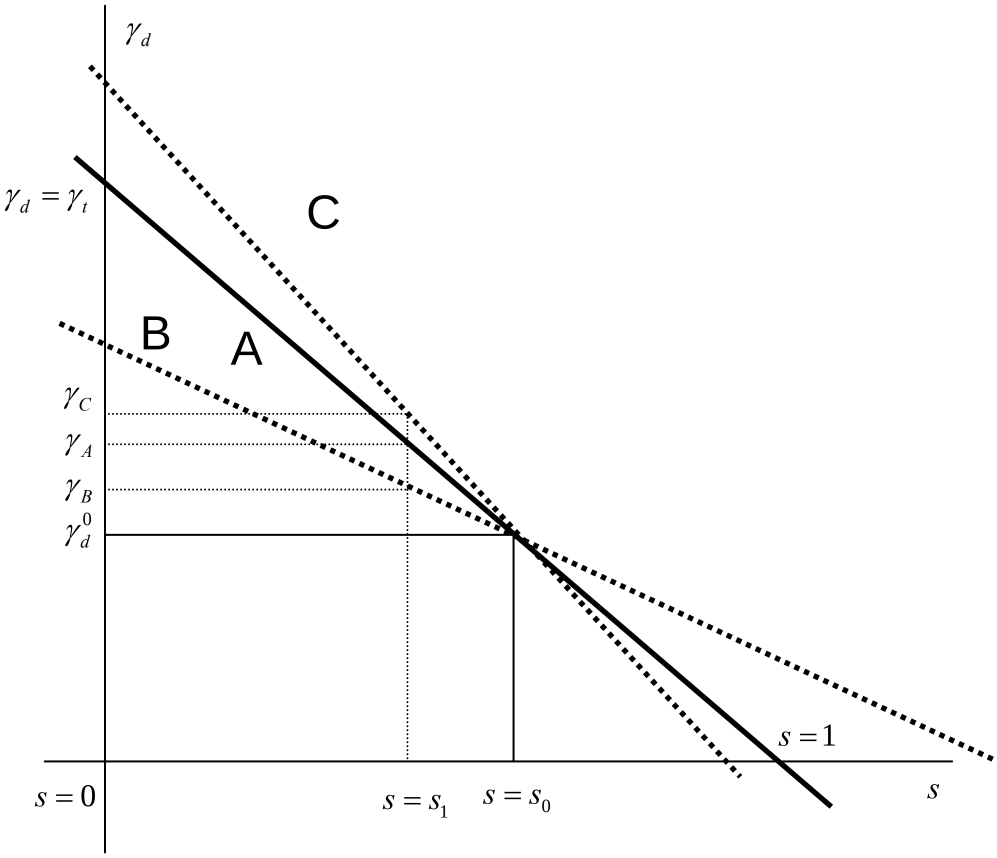

Figure 4: Elasticity of emission multipliers with respect to shares (s) of imports

Coming back to Table 3, the resulting coefficient of determination is 0.99 for the domestic model and 0.98 for the global one, which is quite satisfactory. All estimated multipliers are significant at the 99% confidence level (18 out of 21) in the domestic model. In the total model, 19 are significant at the 99% confidence level, 2 at the 95% confidence level and finally, 1 at the 92% confidence level. Eventually, we have carried out a macro check to test the robustness and coherence of the results. In equation (5), we have replaced C by our estimated (domestic) emission multipliers (γ) and the official net output matrix ($V^{T} - U$). As a result, the estimated direct emissions yield 59,101 thousand tonnes of carbon dioxide, which is only 4.3% greater than the published total emissions (56,661 thousand tonnes). For the total model, the estimated emissions are 3.60% lower than published total emissions (227,724 thousand tonnes).

6 Conclusions

Input-output economics and industrial ecology, particularly LCA, are increasingly joining efforts to quantify national and global environmental impacts of sustainable production and consumption strategies of governments. Hence, the extended use of the Leontief quantity model and the Leontief inverse by IO-LCA practitioners deserve some further thinking on the stochastic limitations derived from the IO literature.

The output multipliers obtained through the Leontief inverse are positive and significantly biased and that is originated from the assumption of a stochastic nature either on the technical coefficients or on the elements of a transaction table (IOT). Needless to say, emission multipliers computed from biased output impact levels generate even more serious overestimation of the emission impacts.

Therefore, this paper provides a new approach to estimate unbiased and statistically consistent emission multipliers. This approach has three important advantages: (a) improve the accuracy of the environmental impacts assessed by industrial ecologists; (b) finds a way to compute unbiased and consistent input-output multipliers for the IOA community; and (c) the use of the Leontief inverse is not needed any more; only the supply and use matrices are required, thus circumventing also the problem of the choice of method in the construction of technical coefficients and/or input-output tables.

With data on the Danish economy and carbon dioxide emissions for 2003, we estimated domestic emission multipliers and compared them with respect to the traditional approach (Leontief inverse). The results confirmed the positive and significant bias reported in the recent literature. Finally, this paper analyses the performance of the Danish sectors in reducing carbon dioxide emissions via external trade. The most eco-efficient sectors in transmitting emissions abroad via importing foreign products are: water transport (18); office machinery and computers (12); machinery and equipment (11); food products (05) and chemicals, rubber and plastics (08). Particularly, it is useful to bear in mind that domestic emission multipliers may vary according to different import shares and that elasticities definitely play a relevant role in the reduction capacity of a sector via external trade.

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