Underestimation of the performance of the EU carbon dioxide emission reductions via external trade

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

Abstract

This paper deals with the identification of appropriate measures of the performance of the European Union in reducing its carbon dioxide emissions via external trade, both at the aggregate and at the industry levels. We have found that standard measures based on the Leontief quantity model and profusely used by input-output practitioners and industrial ecologists will result in underestimation of the actual performance of the EU in reducing its carbon dioxide emissions via external trade. Briefly, standard measures currently available in the literature seem to assign the EU less amounts of exported air emissions (carbon dioxide) than it should be. However, this rule does not hold for all industries individually. From a methodological viewpoint, the conclusions are justified by a new approach to estimate unbiased and statistically consistent emission multipliers. This approach has three important advantages: (a) it improves the accuracy of the environmental impacts assessed by industrial ecologists; (b) it finds a way to compute unbiased and consistent input-output multipliers for input-output analysts; and (c) the use of the Leontief inverse is no longer necessary; only the supply and use matrices are required. In addition, another advantage of this approach is that all the data needed to make the calculations are ready to use worldwide at many countries' statistical offices.

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

1 Background

Sustainable consumption and production is currently a challenging issue on the policy agenda of the European Union (EU). At the World Summit on Sustainable Development (WSSD) in 2002, all countries committed themselves to promoting sustainable patterns of consumption and production, with developed countries taking the lead. More specifically, countries committed to promoting the development of a ten-year framework of programmes on sustainable consumption and production, in support of national and regional initiatives. In March 2003, the European Council (the EU Heads of State or Government) identified sustainable consumption and production and the development of the ten-year framework as one of the key priorities for the EU in the follow-up to the WSSD. This was re-emphasised in the Commission Communication 'The World Summit on Sustainable Development one year on: implementing our commitments' (EU, 2003a) where sustainable consumption and production is one of three overarching objectives. Achieving more sustainable consumption and production patterns is therefore first and foremost an EU internal challenge. The overarching goal of the EU Thematic Strategy on the Sustainable Use of Natural Resources (EU, 2004) is to de-couple environmental impacts associated with the use of natural resources from economic growth, in support of sustainable development. To achieve this, the Strategy is likely to provide a framework and measures that allow resources to be used in a sustainable way without further harming the environment. It is likely to be based on three core tasks: gathering and keeping up-to-date information; assessing policies that directly or indirectly affect resources; and identifying appropriate measures, which will primarily be integrated into other policies. This paper particularly deals with the latter core task, i.e. the identification of appropriate measures of the performance of the EU in reducing its carbon dioxide emissions via external trade, both at the aggregate and at the industry levels.

The reduction of carbon dioxide (CO_2) emissions is considered one of the main objectives of the EU Sustainable and Production Strategy. Consequently, major efforts are being undertaken by European governments to reduce the amount of carbon dioxide emitted by their own nations (see in EU (2004) several descriptions of interesting experiences carried out in the EU Member States). The most challenging issue in planning attempts to reduce carbon dioxide emissions occurs in identifying which activities are the most polluting or which products consumed by final users are the most environmentally harmful. The environmental impact of final consumption was already expressed by Leontief (1970) as an undesirable externality of the production process (a negative by-product). At this respect, the distinction between production and consumption-driven emissions is crucial within the international policy context. For instance, final users from one developed country may demand emission-intensive products from developing countries (via external trade) in order to reduce their own emissions. During this process, the developed country will emit less, but at the cost of an increase in emissions by the developing country to satisfy this new demand. In the end, the net global effect might well be an increase in emissions rather than a reduction, even though the developed country will be able to argue for the achievement of certain emission reduction goals. Hence, in order to clarify environmental responsibilities at the country level, total emissions must be decomposed into two groups: emissions generated by the consumption of goods and services produced domestically and emissions associated with imports, the latter of which is of extreme relevance to the current global policy agenda.

Moreover, the relevant figures should take into account not only direct emissions but also those indirectly emitted by supplier industries in order to produce a certain commodity.

Ideally, a full information on bilateral trade statistics at the industry detailed level and also on the different technologies of production of each of the Member States of the EU together with appropriate NAMEA-based environmental physical accounts on air emissions (e.g. carbon dioxide) would suffice to quantify the air emissions exported by each country via external trade by means of multi-regional input-output analysis (Miller and Blair (2009) is a standard reference on the state-of-the-art of input-output analysis: its foundations and extensions). Nevertheless, the availability of these kinds of data is still very limited and does not allow such type of analysis. Although there are major efforts being currently done by the European Commission to solve these important data drawbacks, namely the two EU-funded international research projects EXIOPOL (www.feem-project.net/exiopol/) and WIOD (www.wiod.org), their outcomes are still on the way.

At this point, this paper provides an alternative (and rather more complementary than exclusive) measure of the performance of the European Union (or any country at hand) in reducing its carbon dioxide emissions via external trade on the basis of a previous work published by Rueda-Cantuche and Amores (2010). In other words, this paper will provide a ratio of performance that measures at the industry level how far the current productive structure of an economy is from its maximum polluting capacity with a given domestic technology. This approach is perfectly in line with Leontief's (1953) approach, the main purpose of which is to compute not the labour/capital consumption of the rest of the world, but the labour/capital saved by the US through imports. Accordingly, our purpose will be to estimate the carbon dioxide emissions saved by the EU through imports and not to compute the emission intensity of the rest of the world. Hence, it seems sensible to take for granted the domestic technology assumption for the reduction in emissions by the EU through imports. Otherwise, imported products should have been produced domestically. This approach may be criticised for not being too realistic, but this would be true only if we wished to measure international emissions, which is not the purpose of this paper. The assumption of domestic technologies in imports in order to account for saved emissions, is already implicit in Dietzenbacher and Mukhopadhyay (2007) and Rueda-Cantuche and Amores (2010). The former authors proved, at least for India, that the pollution avoided by increasing imports is much greater than the pollution generated as a result of increasing exports, which incidentally turned out to be a new green Leontief paradox according to the authors.

Moreover, this paper will also prove that the standard measures available in the literature would underestimate the ratio of performance and thus, would assign the EU less amounts of exported air emissions (carbon dioxide) on average. In addition, another advantage of this approach is that all the data needed to make the calculations are ready to use worldwide at many countries' National Statistical Institutes websites. Notice however that this paper deals particularly with the EU as a whole and benefited from the joint work developed by Eurostat and the Joint Research Centre's Institute for Prospective and Technological Studies of the European Commission for the compilation of the necessary EU aggregate data, which has already been partially published in Rueda-Cantuche, et al. (2009)

The paper is structured as follows. The next section briefly presents the current methodological framework under which input-output economists and industrial ecologists account for environmental impacts, with a particular focus on carbon dioxide emission multipliers. Section 2 also discusses 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. Section 4 provides a new ratio of the performance of the EU's reduction of carbon dioxide emissions via external trade. Section 5 presents briefly the process of compilation of the aggregate supply and use tables of the EU economy (2000) and Section 6 compares on empirical grounds the results of the standard and econometric approaches. The last section concludes the paper, with a summary of the most important findings.

2 Methodological framework

2.1 Industrial ecology and input-output analysis

Following Suh and Kagawa (2005), recent developments have made Life Cycle Assessment (LCA), a key subfield of industrial ecology, one of the areas that most extensively use input-output analysis (IOA). LCA can be thought of as a tool that allows for the quantification and evaluation of the environmental impact of a product over the course of its entire life cycle (Guinée et al., 2002). Another area where IOA is deeply linked to industrial ecology is the product policy field. The European Commission adopted a communication (EC, 2003b) that identified products with the greatest potential for environmental improvement by considering IO-LCA as one of the approaches best suited to implement the European Integrated Product Policy analyses (Suh and Kagawa, 2005; Weidema et al. 2004; Tukker et al. 2005). The rapid generalisation and evolution of systems such as Systems of Environmental and Economic Accounts (SEEA) and National Accounting Matrices including Environmental Accounts (NAMEA) (for instance, Haan and Keuning, 1996; EC, 2001; UN, 2003) also provide an international accounting framework in which input-output tables are supplemented by an increasing number of natural resource accounts (land, water, forestry, etc…) and environmental emissions at the industry level. IOA is also rapidly broadening its scope of application to industrial ecology by extending the analysis to a global level. For instance, the World Trade Model developed by Duchin (2005) and extended by Strømman et al. (2005) has been used to examine the global implications of changes in agricultural land yields due to future climate change (Juliá and Duchin, 2005).

As far as we know, 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 amounts of products consumed by final users, the Leontief quantity model yields variations in industry outputs (considering industry-by-industry IO tables). Therefore, the emission coefficients per unit of industry output generally provided by LCA practitioners and/or NAMEA accounts are to be used to determine the variation in air emissions resulting from the initial final demand change.

Emission multipliers have been reported in a number of studies. Proops et al. (1993) conducted a comparative study of the German and British cases, whereas Östblom (1998) addressed the environmental outcome of emissions-intensive economic growth in the Swedish economy. Lenzen (1998) investigated 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; Haan (2001) developed a structural decomposition analysis of pollution in the Netherlands; Creedy and Sleeman (2005) addressed emission reductions in New Zealand; Lenzen et al. (2004) developed a multi-regional model to compute emission multipliers and emission balances; Alcántara and Roca (1995) analysed primary energy requirements and carbon dioxide emissions during the 1980–1990 period; Llop (2007) decomposed total changes in emission multipliers to account for changes in emission coefficients (polluting intensity) and changes in technical coefficients (economic structure) and more recently, Rodríguez-Morilla et al. (2007) computed the emission multipliers of greenhouse effect gasses using Social Accounting Matrix and Environmental Accounts (SAMEA).

2.2 The concept of unbiasedness in Econometrics

We show briefly in this sub-section the general concept of unbiasedness within an econometric framework. We hope this general introduction to basic Econometrics will help the reader to follow next sub-sections on stochastic input-output analysis.

Generally speaking, the error term (u) in a multiple linear regression model, e.g., $y = a + bx + cz + u$, includes various factors that cannot be explicitly incorporated as explanatory variables for the following motivations: (*a*) the functional form (i.e., linear) may not be the most appropriate; (*b*) the theory explaining the explained variable may be incomplete, with omitted relevant variables; (*c*) perhaps the variables are correctly specified by the theory, but there are no data available or they are difficult to quantify; (*d*) human behaviour is often random and may arbitrarily influence the explained variable; (*e*) there could be errors of measurement; and (*f*) there could be sampling errors. Consequently, the error term is thought of as the composite of a number of (hopefully) minor influences on the explained variable. Nonetheless, we will assume that the error term only includes sampling errors by assuming a linear and correctly specified model without relevant omitted variables, and that the randomness of human behaviour and the errors of measurement do not significantly affect the results.

Accordingly, we will regress direct industry carbon dioxide emission levels (explained variable) on the net outputs of different products (explanatory variables), allowing for an error term that takes into account all the deviations of the actual data (carbon dioxide emission levels) from those estimated by the deterministic part ($a + bx + cz$) and only derived from sampling errors. The estimations will be carried out using ordinary least squares (OLS). This method guarantees that the OLS estimated coefficients (emission multipliers) are the best linear unbiased estimates according to the Gauss-Markov theorem (Greene, 2008). That is, the OLS estimates are unbiased in the sense that if we ever happen to use a set of all possible and exclusive samples of the firms populating a given economy to run the same regression, the expected values of the various OLS coefficients derived from each one of them will match the true values of the unknown parameters of the regression. To the contrary, if one only had one single sample of firms to compile the official supply-use and input-output tables (as it is in practice) and did not allow for sampling errors (u) in the calculation of impacts or any kind of multiplier (e.g. by using the Leontief inverse), then this would be implicitly equivalent to assume that official statistics provide nothing else than the true values of the supply-use and input-output systems with just one single sample!. Bearing this in mind, the use of the Leontief inverse to calculate emission multipliers will lead to biased estimates of emission multipliers just because they simply assume that there are no sampling errors (u) and that the figures depicted in the supply-use tables are precisely the true values. We find this argument not very much acceptable and propose in this paper the inclusion of stochastics in the analyses of emission multipliers to be carried out by industrial ecologists and input-output economists.

2.3 Stochastic input-output analysis

While many studies provide estimations of environmental impacts, as far as we are concerned IO-LCA practitioners have paid little attention to the positive and significant bias of the impact multipliers derived from the Leontief inverse (Dietzenbacher, 2006). Assuming a stochastic technical coefficients matrix, A, leads to the central result that the Leontief inverse, L, is positively biased, with input coefficients that are totally independent (Simonovits, 1975), biproportionally stochastic (Lahiri, 1983) or moment-associated (Flam and Thorlund-Petersen, 1985). That is, denote the true value of a stochastic IO matrix A as A_0 and that of its Leontief inverse L as L_0. Suppose the expected value of A equals A_0 as $E(A) = A_0$ (unbiasedness of the technical coefficients). Consequently,

$$E(L) = E[(I - A)^{-1}] > [I - E(A)]^{-1} = (I - A_0)^{-1} = L_0$$

In practice, even if we happen to dispose of an unbiased matrix A and use the true value of A, the derived multiplier matrix $(I - A_0)^{-1}$ – see right hand side of the inequality – will not correspond to the true value of L. That would be something like: $E(L) = L_0$ + bias. Notice that L_0 does not correspond to $(I - A_0)^{-1}$ but to the true value of L. The difficulty to deal with the unknown true value of $E[(I-A)^{-1}]$ due to its stochastic nature makes researchers use $[I-E(A)]^{-1}$ instead. In particular, Simonovits (1975) further assumes that $E(A)=A_0=A_t$, being A_t the available matrix of technical coefficients. This explains why he reported in his paper under-estimation of the Leontief inverse when referring to the same inequality as Dietzenbacher does. Hence, even though Dietzenbacher (2006) states over-estimation and Simonovits (1975) under-estimation the reader should be aware that they were referring to the same inequality but from two different points of view. This should not lead the reader to confusion.

To sum up, the Leontief inverse matrix is even positively biased even when the matrix A of technical coefficients is unbiased. Nevertheless, this is not the case in practice. The usual estimator of $E[(I-A)^{-1}]$ is given by $L_t=(I-A_t)^{-1}$, which does not use A_0 but a technical coefficient matrix that has been estimated by sampling methods (A_t). So, the bias might be even larger than that of A_0. The expectation of L_t should be L_0 + bias, but notice that the bias here is different from the bias mentioned previously in $E(L)$. Denote the econometric (unbiased) estimator of the Leontief inverse as L_e so that $E[L_e]= L_0$. It follows that the bias of the standard Leontief inverse can be calculated by $E(L_t)-E(L_e)$, and following ten Raa and Rueda- Cantuche (2007) we estimated this bias as $L_t - L_e$.

As Dietzenbacher (2006) argues, the overestimation of the multipliers is not a negligible issue. Because the Leontief inverse is usually post-multiplied by an exogenously specified (positive) final demand vector, all separate positive biases accumulate in the projection of output levels and even more on emission multipliers. Dietzenbacher (2006) also recommended assuming stochastics on the symmetric input-output table (IOTs) values rather than on the input coefficients. Although more plausible from an economic viewpoint, this approach has rarely been adopted (Gerking, 1976, 1979; and Dietzenbacher, 1988). The reason for the rarity of this approach is likely that the additional step of transforming intermediate uses into input coefficients seriously complicates the analysis, typically producing input coefficients of a rather complex stochastic nature.

Alternatively, ten Raa and Rueda-Cantuche (2007) computed unbiased estimates of the column row sums of the Leontief inverse (backward multiplier estimates) directly from supply and use firms' data. Their study assumed that total output and employment (firms) data used to compile the official supply and use tables were stochastic. The supply and use tables incidentally form the preparatory step for constructing an IOT. These authors proposed a single-equation econometric model in which the regression coefficients result in the output (and employment) multipliers obtained through the Leontief inverse, using the product technology assumption for the construction of the input coefficients matrix A. The authors estimated output and employment multipliers and compared them with those obtained through the Leontief inverse. The results confirmed the positive expected bias on almost all of the significant multipliers, in addition to some with values that were not as negligible.

Apart from the problem of quantifying the positive bias, the main advantage of this approach is that unbiased and consistent multipliers can be estimated for further application to the calculation of emission variations due to changes in final demand quantities. Furthermore, this approach allows for the estimation of confidence intervals for the emission multipliers and standard hypotheses tests. However, this approach is significantly limited by data availability at the firm level. More recently, in order to circumvent this issue Rueda-Cantuche and Amores (2010) shifted the analysis to supply and use tables and carried out the analysis for Denmark. This paper eventually extends the latter to the European Union and, in addition, discusses the repercussions of Leontief-based biased emission multipliers on its performance in reducing carbon dioxide emissions via external trade.

2.4 Supply-use and input-output tables

A relevant issue in the estimation of input coefficients is the technology assumption to be assumed for the compilation of the IOT if it is product-by-product (for a review, see ten Raa and Rueda-Cantuche, 2003). The same applies for industry-by-industry IOTs provided two alternative delivery assumptions (Eurostat, 2008). A vast body of literature has detailed a long-standing controversy regarding the best method of compiling IOTs on theoretical grounds. On one hand, Kop Jansen and ten Raa (1990) have proven that the product technology assumption (i.e., that all products are produced in the same way irrespective of the producer industry) is the best method of compiling product-by-product tables. On the other hand, Rueda-Cantuche and ten Raa (2008) recently proved that for industry-by-industry tables, the superior method is the fixed industry sales structure assumption—i.e., constant deliveries of industries irrespective of the products they sell.

2.5 Contributions

This paper continues the line initiated by Rueda-Cantuche and Amores (2010) when they first combined the use of econometric modelling tools within a supply-use system to address environmental repercussions (carbon dioxide emissions) of changes in the amounts consumed by final users. This approach provides one-shot unbiased and consistent estimates of carbon dioxide emission multipliers on the basis of official supply and use tables. The method also provides confidence intervals for emission multipliers. Under this approach, a Leontief inverse is no longer necessary to estimate emission impacts. Accordingly, IO-LCA practitioners would be able to estimate statistically significant impacts using only published supply-use tables (both at basic prices), data on direct emissions and some standard econometrics. This paper deals with the performance of the EU in reducing (carbon dioxide) emissions via importation of emission-intensive products from other countries.

Following ten Raa and Rueda-Cantuche (2007), the practice of interrelating accounts and input-output multipliers can be deconstructed into three steps. The first step consists of filling data gaps, imputing values to non-observed establishments, and summation over firms within industries. These operations are straightforward and produce the use and make tables U and V (the latter being 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 secondary outputs, all of which will have to be treated in the second step. The result is a matrix of input-output coefficients, A. The third and last step is a Leontief inversion, $(I - A)^{-1} = I + A + A^2 + \dots$. In multiplier analysis, the first term represents the direct effect, the second term the direct input requirement, and the third and following terms the indirect input requirements.

The theory of input-output coefficients centres on the second step and analyses several models for their construction. The results are partial, and problems persist, such as the problem of negative coefficients. The stochastic input-output literature focuses on the third step, analysing the transmission of errors under the Leontief inversion. At this point, nonlinearity adds to the list but not actually associated with secondary production. As mentioned earlier, positive bias are expected in multipliers.

This paper makes two interrelated contributions to the literature. Firstly, the Leontief inverse-based estimates of the carbon dioxide emission multipliers are proven to overestimate the true values of the emission impacts and therefore, mislead the performance measures of emission reductions via external trade. This is done by imposing stochastics on the variability of the supply-use statistics across industries rather than on input coefficients. Secondly, we integrate all the three mentioned steps by reducing the impact multiplier calculations to a single use of a linear econometric model that uses the available supply-use tables instead of the usual symmetric IOT. The non-linearity of the different construction methods used to compute an IOT together with the non-linearity of the Leontief inversion in the calculation of impact multipliers that frustrate the construction of input-output coefficients and transmit errors in the Leontief inverse, neutralise each other upon combination. Thus, we are able to estimate consistent linear unbiased estimates of (emission) multipliers. The application refers to the European Union for the year 2000.

3 Econometric model for determining carbon dioxide emission multipliers

This section aims to describe how carbon dioxide emission multipliers can be estimated econometrically. We will take as starting point the standard input-output formulation for input-output multipliers in the case of carbon dioxide emissions. As in Miller and Blair (2009) 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:

$$\gamma = c(I - A)^{-1}, \qquad \textbf{(1)}$$

where c denotes a row vector of direct carbon dioxide emission coefficients and $(I\text{-}A)^{-1}$ 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 amounts consumed by final users of a certain commodity. Next, according to the product technology assumption by which direct carbon dioxide emissions of a commodity in absolute values are independent of the producing industry, we denote

$$C = cV^T$$
$$c = CV^{-T} , \qquad \textbf{(2)}$$

where C stands for a row vector of direct industry carbon dioxide emission levels and V^T (the transpose of the intermediate matrix of a make table) for a production matrix of the supply table at basic prices. Similarly, the construction of the input matrix A under the product technology assumption is given by

$$U = AV^T$$
$$A = UV^{-T} , \qquad \textbf{(3)}$$

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

$$\gamma = CV^{-T}(I - UV^{-T})^{-1} = C[(I - UV^{-T})V^T]^{-1} = C(V^T - U)^{-1}, \qquad \textbf{(4)}$$

which can be rearranged as

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

If there were the same number of industries and products, equation (5) would simply become a system of equations with just a single solution for the γ coefficients. Nevertheless, rectangular systems typically derived from supply and use tables usually have different number of industries and products and thus allow for the introduction of a random disturbance error ε.This error term can thus be defined as a row vector of m independent and normally distributed errors with zero mean and constant variance:

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

Subsequently, the emission multipliers result to be stored in a vector of regression coefficients, γ. In equation (6), C is an m-order row vector (m industries) of direct carbon dioxide emissions, γ corresponds to an 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 (product by industry).

Notice that m represents the number of industries and also the number of observations. Moreover, the net output of commodities (n) would be the explanatory variables of the derived model. In order to get enough degrees of freedom, we need to have more industries than products in our equation system ($m>n$). However, rectangular supply and use tables (SUTs) are rarely available in official statistics although they are compiled originally from a rectangular system where business establishment reports on inputs and outputs are organized in worksheets, which are essentially disaggregated supply and use tables (ten Raa, 2005). So, from square SUTs one can have more industries than products by two ways, i.e.: either aggregating products or splitting up industries. In the absence of more available data, the simplest way to proceed is clearly the former option while the latter would require more detailed information on inputs and outputs that statistical offices very seldom report. This justifies our decision to aggregate products instead of breaking down industries in order to obtain enough degrees of freedom.

Concerning the differences between the econometric estimations and the Leontief inverse-based calculations, Rueda-Cantuche and Amores (2010) proved that the econometric estimations of the emission multipliers obtained from equation (6) will match those calculated with equation (1) only when the number of industries equals the number of products. In other words, if one assumes complete absence of stochastic errors in equation (6), which should not be necessarily true, then one must always use square SUTs. Therefore, our econometric approach is definitely oriented to rectangular supply-use systems rather than to square systems, for which the two approaches would not make any difference.

4 Measuring the performance of emission reductions via external trade

Suppose the simplest case of one economy with just one single sector. In National Accounts, the total product output x would result from the sum of the intermediate use of products produced domestically (z_{d}), the imported intermediate uses (z_{m}) and final demand, y (including final consumption, investment and exports). In mathematical terms,

$$x = z_{\mathrm{d}} + z_{\mathrm{m}} + y\,. \tag{7}$$

Equation (7) can be transformed into:

$$x = a_{\mathrm{d}}x + z_{\mathrm{m}} + y$$

being a_{d} the domestic input requirements per unit of product output (z_{d}/x). Subsequently, $(1-a_{\mathrm{d}})x = z_{\mathrm{m}} + y$ and therefore,

$$x = \frac{z_{\mathrm{m}} + y}{1-a_{\mathrm{d}}} = \frac{z_{\mathrm{m}}}{1-a_{\mathrm{d}}} + \frac{y}{1-a_{\mathrm{d}}}$$

Consequently, the change in product output (Δx) per one-unit variation in final demand yields:

$$\frac{\Delta x}{\Delta y} = \frac{1}{1-a_{\mathrm{d}}}$$

and provided that c_{o} stands for the amount of carbon dioxide emitted per unit of product output, the domestic emission impact resulting for each one-unit change in final demand would be:

$$c_{\mathrm{o}}\frac{\Delta x}{\Delta y}=\frac{c_{\mathrm{o}}}{1-a_{\mathrm{d}}},$$

which, for a multiple n-dimension economy, is actually:

$$\gamma_{\mathrm{d}}=c\left(I-A_{\mathrm{d}}\right)^{-1}$$

being c the so called emission coefficients vector.

If one assumes now that all imports of good and services were to be produced domestically, then z_{m} = 0 and hence, z_{d} = z. Consequently, equation (7) could also be expressed as $x=ax+y$, being a the total input requirements per unit of product output (z/x). Similarly, the change in product output (Δx) per one-unit variation in final demand (Δy) yields:

$$\frac{\Delta x}{\Delta y}=\frac{1}{1-a}$$

and given that c_{o} stands again for the physical amount of carbon dioxide emissions emitted per unit of product output, the domestic emission impact resulting for each one-unit change in final demand would be:

$$c_{\mathrm{o}}\frac{\Delta x}{\Delta y}=\frac{c_{\mathrm{o}}}{1-a},$$

which, for a multiple n-dimension economy, can be expressed as:

$$\gamma=c\left(I-A\right)^{-1}.$$

Since a is expected to be always greater or equal than a_{d}, then it is straightforward that:

$$\frac{1}{1-a}\geq\frac{1}{1-a_{\mathrm{d}}}$$

and eventually, in matrix terms, this is similar to $c\left(I-A\right)^{-1}\geq c\left(I-A_{\mathrm{d}}\right)^{-1}$ and hence, $\gamma\geq\gamma_{\mathrm{d}}$.

In other words, γ can be considered a measure of the maximum polluting capacity (per one-unit increase in final demand quantities) of an economy. If all imported products were produced domestically, γ would yield how much carbon dioxide emissions were to be increased (per one physical unit of final demand) to reach the maximum level of emissions for a given domestic technology. However, in the real outside world, countries indeed import, and emissions are transferred abroad via external trade. Therefore, if one considers domestic intermediate uses, then γ_d would be just a measure of the actual polluting capacity calculated by taking into account only domestically produced inputs.

Because γ_d is expected to be benchmarked by γ, we define the following ratio of performance (P) that measures at the industry level how far the current productive structure of an economy is from its maximum polluting capacity. The ratio of performance, P, is defined as follows:

$$P = 1 - \frac{\gamma_d}{\gamma}. \quad \textbf{(8)}$$

For example, if γ_d is equal to 10 tonnes and γ is equal to 20 tonnes (P=1-10/20 = 0.5) for a certain product, then the European importation of such commodities allows the EU to use only 50% of its maximum polluting capacity per unit of final demand. It is straightforward that as long as the P value gets closer to 1, then the emissions of the corresponding industry are being reduced via external trade (imports). The opposite applies to values of P close to 0.

This ratio of performance is clearly independent of the way domestic and total impact multipliers (γ and γ_d) are estimated but however, the use of the Leontief inverse or the econometric approach proposed in this paper will make a difference with respect to the unbiasedness of the emission multipliers. Similarly, using equation (6) from the previous section, the alternative econometric estimations of γ and γ_d would be given by running ordinary least squares in the two following linear regressions:

$$C = \gamma_{\mathrm{d}}(V^T - U_{\mathrm{d}}) + \varepsilon_{\mathrm{d}} \quad \textbf{(9)}$$

$$C = \gamma(V^T - U) + \varepsilon \quad \textbf{(10)}$$

being U and U_d the domestic and total intermediate uses, respectively, and ε and ε_{d} two normally distributed random disturbance errors with zero mean and constant variance.

5 EU27 aggregated supply and use tables (2000)

In one of my previous works (Rueda-Cantuche et al, 2009), the very first EU27 aggregate (product by product) input-output table (EU27-IOT) at basic prices was compiled for the year 2000. The EU27-IOT distinguishes between domestic and imported (from third countries) uses. The interested reader may find more details on its construction in Rueda-Cantuche et al (2009). The EU27-IOT would suffice to calculate the Leontief-inverse based emission multipliers but however, our approach requires the use of supply-use tables to run equations (9) and (10), which are not directly available.

As regard the EU27 aggregate supply table for 2000, all supply tables from individual Member States are publicly available through the Eurostat website except for Cyprus. Consequently, we had to apply the Greek supply matrix structure as a proxy to complete the list. We are convinced that provided the size of the Cypriot economy within the EU, the error we make by imposing this assumption will not alter dramatically our final results. Eventually, the EU27 aggregate intermediate supply matrix (V^T) is compiled by merging the twenty-seven individual supply tables.

Following the Eurostat Manual of Supply, Use and Input-Output Tables (Eurostat, 2008, p. 352), one can derive a use table at basic prices from: (a) an input-output table at basic prices (either of a product by product or industry by industry type); and (b) a supply table at basic prices. As a result, we derived both the domestic and the total use matrices at basic prices from the following expressions (e denotes a column vector of ones):

$$U = Z * \left[\mathrm{diag}(V^T e)\right]^{-1} V^T \quad \textbf{(11)}$$

$$U_{\mathrm{d}} = Z_{\mathrm{d}} * \left[\mathrm{diag}(V^T e)\right]^{-1} V^T \quad \textbf{(12)}$$

being Z and Z_{d} the corresponding total and domestic intermediate uses of the EU27-IOT. By using equations (11) and (12), we are implicitly assuming a product technology assumption in the construction of the EU27-IOT, which means that all products are produced in the same way irrespective of the industry that actually produces them. One of the main advantages of this assumption when one reverses supply and use tables from symmetric IOTs is that it does not yield negative values. Notice, however, that vice versa is completely the other way round.

6 Results

The empirical work was carried out for the EU economy as a test case with supply and use tables (SUTs) for the year 2000 (59 industries/commodities) valued at basic prices and expressed in millions of euros at current prices. Up to 21 pollutant-wise groups of commodities were aggregated in order to obtain sufficient degrees of freedom (59 industries – 21 commodities = 38 degrees of freedom) to estimate equations (9) and (10). The definite number of degrees of freedom in each equation may be slightly modified due to the presence and correction of outliers.

The model was estimated by the Ordinary Least Squares (OLS) method. Due to the presence of certain forms of unknown heteroskedasticity, the White estimate (White, 1980) of the variance and covariance matrices of the estimated coefficients was used to provide consistent and robust standard errors. No autocorrelation problems (as expected in cross-sectional data) or multicollinearity problems plagued our analysis. For the total model, only 1 out of the 210 (0.48%) possible off-diagonal elements of the matrix of correlations with 21 different explanatory variables was larger than 0.5, and none was greater than 0.75. In the domestic model, all correlation coefficients were below 0.5.

For comparison purposes, the Leontief inverse-based emission multipliers were not constructed on the basis of the EU27-IOT but on a pure product technology basis for the aggregated 21 sectors/products—e.g., in the input matrix $A_{21\mathrm{x}21}$. This means that equation (1) was computed using an aggregated version of the EU27-$SUT_{59\mathrm{x}59}$ and the product technology model, as expressed in equation (3).

Eurostat publishes regularly NAMEA (environmental) accounts for all twenty-seven EU Member States and the EU as a whole. Hence, we used published official data on the direct carbon dioxide emissions. This publication presents data on industry emissions with a breakdown of 59 NACE industries or economic activities. Table 1 shows the industries with the highest direct emissions in the European Union. Table 1 does not include the emissions generated abroad by foreign products imported by the EU.

Table 1.
Domestic direct emissions in the EU (2000)
Source: Eurostat

Code	Industry	Domestic direct emissions (Thousands of CO_2 tonnes)	Domestic direct emissions (percentage)
01	Agriculture, hunting and related services	95,422.8	2.9%
02	Fishing and other fishing; services incidental of fishing	10,777.7	0.3%
03	Mining of coal, uranium and other mining and quarrying products	31,672.5	1.0%
04	Extraction of Crude petroleum & natural gas; and incidental related services	32,990.0	1.0%
05	Manufacture of food products and beverages; Tobacco	74,596.3	2.2%
06	Manufacture of textiles, leather, wood, cork, pulp, paper and paper products	86,845.7	2.6%
07	Manufacture of coke, refined petroleum products and nuclear fuels	154,585.1	4.6%
08	Manufacture of chemicals, rubber and plastics	173,172.0	5.2%
09	Manufacture of other non-metallic mineral products	240,467.2	7.2%
10	Manufacture of metallurgy and fabricated metal products	252,594.9	7.6%
11	Manufacture of machinery and equipment; electrical machinery & apparatus	26,004.7	0.8%
12	Manufacture of office mach. & computers; radio, TV & communication equip. medical & precision intruments; transport equip.	35,750.3	1.1%
13	Manufacture of furniture; other manufactured goods; secondary raw materials	19,439.0	0.6%
14	Electricity, gas, steam and hot water	1,348,921.5	40.5%
15	Construction	43,333.3	1.3%
16	Trade; hotel and restaurant services	97,562.5	2.9%
17	Land transport	221,930.1	6.7%
18	Water transport	71,480.7	2.1%
19	Air transport	94,715.8	2.8%
20	Other services	130,818.6	3.9%
21	Public Admin. Education, Health & social work	84,228.9	2.5%

Electricity, gas, steam and hot water generation (14) amount to slightly more than 40% of total emissions, whereas metallurgy and fabricated metal products (7.6%); the other non-metallic mineral products (7.2%); land transport (6.7%); manufacture of chemicals, rubber and plastics (5.2%) and crude petroleum and natural gas (4.6%) account for nearly one third. Ranking in terms of (domestic) direct emission coefficients (tonnes per million of euros) yields different results (see Table 2) for almost all industries except for electricity (14), which has the greatest value (3,275.9 tonnes per million of euros); and other non-metallic mineral products (09), which have the second largest emission coefficient (1,240.3 tonnes). The top-five list is completed by water transport (961.6), the fishing industry (927.5 tonnes); and air transport (841 tonnes). Moreover, when considering direct and indirect (domestic) emissions through the Leontief inverse-based calculations, the top-five list remains unchanged. However, the econometric estimations show that the crude petroleum and natural gas industry (04) and the manufacturing of coke and refined petroleum products (07) have one of the greatest impacts in terms of domestic carbon dioxide emissions.

Table 2.
Domestic carbon dioxide emission multipliers in the EU (2000)
Source: Own elaboration

Code	Commodity	Emission Coefficient	Emission multipliers (Domestic model): Leontief calculation	Econometric. Calculation: Multipliers	p value	CI bounds: lower	CI bounds: upper	estimated bias
		(CO_2 tonnes *per* million of Euro)						
01	Products of agriculture, hunting and related services	260.5	529.6	412.5	0.000	354.8	470.3	117.0
02	Fish and other fishing products; services incidental of fishing	927.5	1,195.1 #	1,029.5	0.000	723.0	1,335.9	165.6
03	Coal, uranium and other mining and quarrying products	579.0	1,013.6 #	735.8	0.014	161.6	1,310.0	277.8
04	Crude petroleum and natural gas; and incidental related services	439.7	547.4	2,351.9	0.000	2,296.1	2,407.7	-1,804.5
05	Food products and beverages; Tobacco	101.7	462.3	162.9	0.000	131.5	194.3	299.4
06	Textiles, leather, wood, cork, pulp, paper and paper products	107.6	410.1	224.8	0.009	60.3	389.3	185.3
07	Coke, refined petroleum products and nuclear fuels	640.9	969.4	1,278.5	0.000	1,254.5	1,302.5	-309.1
08	Chemicals, rubber and plastics	235.2	622.4 #	503.1	0.000	350.3	655.9	119.3
09	Other non-metallic mineral products	1240.3	1,810.1	1,611.2	0.000	1,525.0	1,697.4	198.9
10	Metallurgy and fabricated metal products	416.1	901.4	206.8	0.000	116.4	297.1	694.7
11	Machinery and equipment; electrical machinery & apparatus	38.1	339.3	145.8	0.000	86.4	205.3	193.5
12	Office mach. & computers; radio, TV & communication equip. medical & precision intruments; transport equip.	31.4	328.6	68.2	0.000	35.1	101.4	260.4
13	Furniture; other manufactured goods; secondary raw materials	105.4	432.5	103.8	0.024	14.7	192.9	328.8
14	Electricity energy, gas, steam and hot water	3275.9	4,169.3	5,072.1	0.000	5,033.3	5,110.9	-902.8
15	Construction work	37.9	391.7	96.0	0.000	79.8	112.3	295.6
16	Trade; hotel and restaurant services	46.3	222.3	117.2	0.024	16.4	218.0	105.2
17	Land transport	524.0	721.1 #	734.5	0.000	710.5	758.4	-13.3
18	Water transport	961.6	1,263.4 #	1,245.7	0.000	1,120.6	1,370.8	17.7
19	Air transport	841.0	1,054.9 #	1,020.0	0.000	959.7	1,080.2	34.9
20	Other services	27.5	147.8	227.5	0.000	155.1	299.9	-79.7
21	Public Admin. Education and Health & social work services	40.7	164.9	61.5	0.001	25.5	97.5	103.5

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

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

Note: All the coefficients are significant at the 97% confidence level.

Table 3.
Total carbon dioxide emission multipliers in the EU (2000)
Source: Own elaboration

Code	Commodity	Emission Coefficient	Emission multipliers (Total model): Leontief calculation	Econometric. Calculation: Multipliers	p value	CI bounds: lower	CI bounds: upper	estimated bias
		(CO_2 tonnes *per* million of Euro)						
01	Products of agriculture, hunting and related services	260.5	565.1	454.0	0.000	376.8	531.3	111.1
02	Fish and other fishing products; services incidental of fishing	927.5	1,246.5 #	1,149.8	0.000	619.2	1,680.3	96.8
03	Coal, uranium and other mining and quarrying products	579.0	1,067.8 #	1,005.8	0.008	278.4	1,733.2	62.0
04	Crude petroleum and natural gas; and incidental related services	439.7	563.7	5,606.0	0.000	5,478.1	5,734.0	-5,042.4
05	Food products and beverages; Tobacco	101.7	511.2	178.5	0.000	137.4	219.7	332.7
06	Textiles, leather, wood, cork, pulp, paper and paper products	107.6	462.0	250.8	0.014	53.2	448.4	211.2
07	Coke, refined petroleum products and nuclear fuels	640.9	1,213.1	1,472.9	0.000	1,430.5	1,515.4	-259.8
08	Chemicals, rubber and plastics	235.2	708.8 #	638.0	0.000	387.2	888.8	70.8
09	Other non-metallic mineral products	1240.3	1,869.6	1,713.6	0.000	1,597.1	1,830.0	156.1
10	Metallurgy and fabricated metal products	416.1	1,000.9	246.3	0.000	127.3	365.3	754.6
11	Machinery and equipment; electrical machinery & apparatus	38.1	407.7	187.0	0.000	112.9	261.1	220.7
12	Office mach. & computers; radio, TV & communication equip. medical & precision intruments; transport equip.	31.4	420.9	87.2	0.003	31.2	143.1	333.7
13	Furniture; other manufactured goods; secondary raw materials	105.4	501.6	120.3	0.065	-7.7	248.3	381.3
14	Electricity energy, gas, steam and hot water	3275.9	4,241.7	5,140.8	0.000	5,088.7	5,192.8	-899.0
15	Construction work	37.9	438.3	103.9	0.000	83.0	124.7	334.4
16	Trade; hotel and restaurant services	46.3	244.9	126.0	0.030	12.9	239.2	118.9
17	Land transport	524.0	752.3 #	765.8	0.000	735.0	796.5	-13.4
18	Water transport	961.6	1,327.5 #	1,309.9	0.000	1,118.7	1,501.1	17.6
19	Air transport	841.0	1,119.2 #	1,122.3	0.000	1,022.5	1,222.1	-3.1
20	Other services	27.5	163.9	267.2	0.000	170.7	363.7	-103.3
21	Public Admin. Education and Health & social work services	40.7	182.8	61.7	0.002	24.5	98.9	121.1

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

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

Note: All the coefficients are significant at the 93% confidence level.

Table 2 also shows the extent to which a sector has a large emission multiplier due to the extensive use of intermediate pollutant inputs. Such an overview can be provided by relating the direct emission coefficients to the direct and indirect econometric multipliers. These sectors are typically other services (20); crude petroleum and natural gas (04); machinery and equipment (11); construction work (15); trade, hotel and restaurant services (16), among others.

Table 3 shows that the top-five of (total) direct and indirect emission multipliers is almost identical to that of the direct emission coefficients, i.e. just the crude petroleum and natural gas replace air transportation. Nevertheless, the econometric estimations show that the crude petroleum and natural gas industry (04) and the manufacturing of coke and refined petroleum products (07) also have great impacts in terms of total direct and indirect carbon dioxide emissions. Table 3 also shows the industries with largest total emission multipliers due to an extensive use of intermediate pollutant inputs, i.e.: crude petroleum and natural gas (04); other services (20); machinery and equipment (11); office machinery and computers (12); construction work (15); trade, hotel and restaurant services (16), among others.

From Tables 2 and 3, we have also derived the following considerations from 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, between15 to 16 out of 21 commodities have lower estimated multipliers than those calculated using the traditional approach. Confirming the results reported by Dietzenbacher (2006), the magnitude of the estimated bias tends to be small and positive. Nonetheless, the weighted average (the weights used are the shares of the econometric estimates of emission multipliers) of the positive estimated biases only amounts to between 0.2% and 0.4%, whereas that of the negative biases varies between -3.1% and -6.9%. Similar results were provided by Dietzenbacher (1995), Roland-Holst (1989), ten Raa and Rueda-Cantuche (2007) and Rueda-Cantuche and Amores (2010).

b) Econometric input–output (ordinary least squares) estimates are unbiased and consistent, providing confidence intervals for carbon dioxide emission multipliers. Our confidence intervals provide a range of values for the true emission multipliers in the sense that the true value of the emission multiplier demonstrates a 95% probability (also called confidence level) of belonging to this interval. Obviously, the number of degrees of freedom will affect the amplitude of the interval, making it more precise (with less amplitude) when it has a large number of degrees of freedom. The opposite applies to models with a smaller number of degrees of freedom, in which the confidence intervals may be so wide that it becomes difficult to provide a meaningful range of values. The midpoint of the confidence interval is precisely the unbiased econometric estimate, and the amplitude will depend on the degrees of freedom, the fixed confidence level (e.g., 95%) and the estimated standard errors of the regression coefficients (the interested reader may refer to Greene, 2008). Note that only six multipliers derived from the traditional approach fell within the confidence intervals. That is, only six out of the twenty-one traditional emission multipliers calculated may be sufficiently close to the true value of the parameter with 95% probability.

c) The measurement of the extent to which sectors use intermediate pollutant inputs is also affected by the bias. Because the Leontief inverse-based multipliers are generally overestimated, the use of econometric multipliers may make sectors like office machinery (12) appear to consume emission-intensive inputs when this is not really the case. The same applies to metallurgy and fabricated metal products (10); furniture and other manufactured goods (13) as well as construction work (15). The opposite can be said about crude petroleum and natural gas (04) and other services (20).

In order to test for significant correlations between the different rankings obtained from the econometric and Leontief-based approaches, we computed the Spearman coefficient of correlation, which amounted to 0.83 and was also significant at the 99% confidence level.

Table 4 presents the results of estimated equations (9) and (10) together with the results of the ratio of performance (*P*) given by (8). As expected, domestic emission multipliers are always lower than total emission multipliers. Figure 1 shows that the most eco-efficient sectors in transmitting emissions abroad via external trade are the extraction of crude petroleum and natural gas (including incidental related services) (04); coal mining (03); chemicals, rubber and plastics (08); machinery and equipment (11) and the manufacturing of office machinery and computers and other electronic equipments (12). Public administration, education and health services (21); electricity, gas, steam and hot water (14); land transport (17), water transport (18) and the manufacturing of other non-metallic mineral products (09) reported the lowest values, indicating inefficient reduction of emissions through external trade.

Table 4.

Domestic and total carbon dioxide emission multipliers (summary). Ratio of performance.

Source: Own elaboration

Code	Commodity	Domestic model				Total model				*P*
		Multiplier	CI bounds lower	CI bounds upper	p value	Multiplier	CI bounds lower	CI bounds upper	p value	
01	Products of agriculture, hunting and related services	412.5	354.8	470.3	0.000	454.0	376.8	531.3	0.000	0.09
02	Fish and other fishing products; services incidental of fishing	1,029.5	723.0	1,335.9	0.000	1,149.8	619.2	1,680.3	0.000	0.10
03	Coal, uranium and other mining and quarrying products	735.8	161.6	1,310.0	0.014	1,005.8	278.4	1,733.2	0.008	0.27
04	Crude petroleum & natural gas; and incidental related services	2,351.9	2,296.1	2,407.7	0.000	5,606.0	5,478.1	5,734.0	0.000	0.58
05	Food products and beverages; Tobacco	162.9	131.5	194.3	0.000	178.5	137.4	219.7	0.000	0.09
06	Textiles, leather, wood, cork, pulp, paper and paper products	224.8	60.3	389.3	0.009	250.8	53.2	448.4	0.014	0.10
07	Coke, refined petroleum products and nuclear fuels	1,278.5	1,254.5	1,302.5	0.000	1,472.9	1,430.5	1,515.4	0.000	0.13
08	Chemicals, rubber and plastics	503.1	350.3	655.9	0.000	638.0	387.2	888.8	0.000	0.21
09	Other non-metallic mineral products	1,611.2	1,525.0	1,697.4	0.000	1,713.6	1,597.1	1,830.0	0.000	0.06
10	Metallurgy and fabricated metal products	206.8	116.4	297.1	0.000	246.3	127.3	365.3	0.000	0.16
11	Machinery and equipment; electrical machinery & apparatus	145.8	86.4	205.3	0.000	187.0	112.9	261.1	0.000	0.22
12	Office mach. & computers; radio, TV & communication equip. medical & precision intruments; transport equip.	68.2	35.1	101.4	0.000	87.2	31.2	143.1	0.003	0.22
13	Furniture; other manufactured goods; secondary raw materials	103.8	14.7	192.9	0.024	120.3	-7.7	248.3	0.065	0.14
14	Electrical energy, gas, steam and hot water	5,072.1	5,033.3	5,110.9	0.000	5,140.8	5,088.7	5,192.8	0.000	0.01
15	Construction work	96.0	79.8	112.3	0.000	103.9	83.0	124.7	0.000	0.08
16	Trade; hotel and restaurant services	117.2	16.4	218.0	0.024	126.0	12.9	239.2	0.030	0.07
17	Land transport	734.5	710.5	758.4	0.000	765.8	735.0	796.5	0.000	0.04
18	Water transport	1,245.7	1,120.6	1,370.8	0.000	1,309.9	1,118.7	1,501.1	0.000	0.05
19	Air transport	1,020.0	959.7	1,080.2	0.000	1,122.3	1,022.5	1,222.1	0.000	0.09
20	Other services	227.5	155.1	299.9	0.000	267.2	170.7	363.7	0.000	0.15
21	Public Admin. Education and Health & social work services	61.5	25.5	97.5	0.001	61.7	24.5	98.9	0.002	0.00

Key: p value = 0.000: p values less than 10^{-4} are rounded down to 0.000, but are different from zero.

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

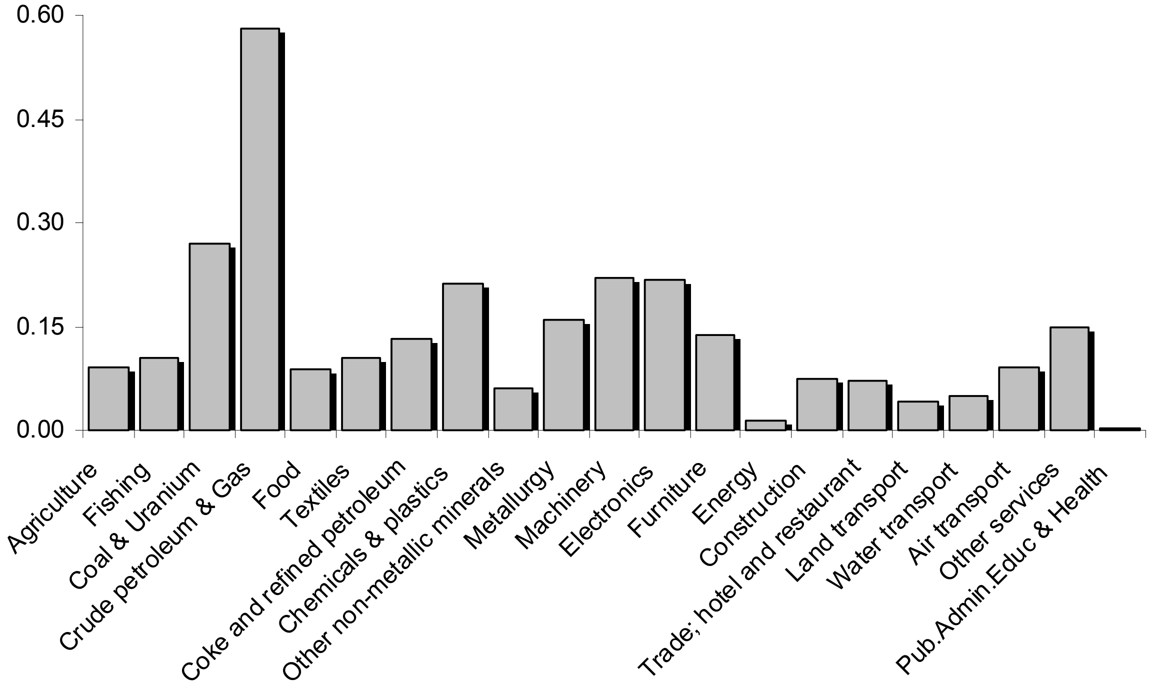
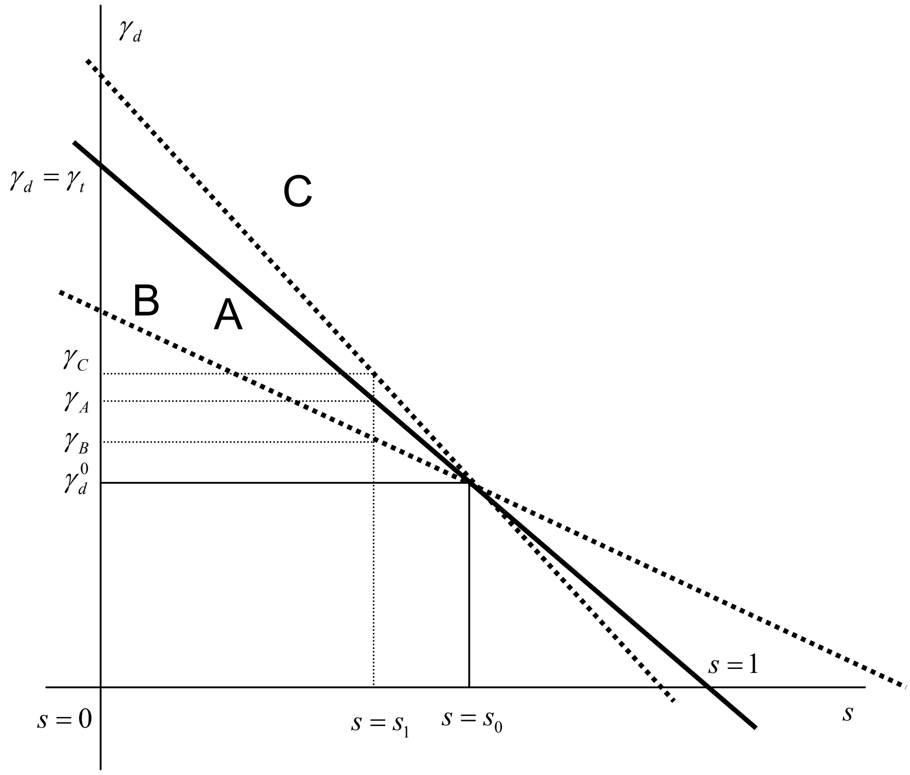


Fig. 1. Ratio of performance, *P* (using econometric emission multipliers).

Note that the larger the share of imports, the larger the expected performance score (with a maximum of 1). External trade indeed influences the reduction of emissions in sectors like crude petroleum and natural gas (04), coal mining (03) and chemicals, rubber and plastics (08). Other sectors, like public administration, education and health services (21), energy (14) and land transport (17), have small shares of imports and, therefore, small values of *P*. Nevertheless, we may find specific industries with a large share of imported primary products but low values for *P*—or, in other words, products that are not performing very well in the transfer of emissions abroad via external trade (e.g., fishing activities (02) and textiles (06)). In contrast, the other services category (20) and construction (15) display small shares of imported services, but that share is sufficient to keep this category far from its maximum polluting capacity. In this respect, it is useful to keep in mind that domestic emission multipliers may vary according to different import shares and that their elasticity plays an important role (see Figure 2).

Figure 2 represents the way in which import shares and emission multipliers may be related. When all imports are produced domestically (s=0 and P=0), total emission multipliers match domestic emission multipliers. In contrast, if everything is imported, then the domestic emission multiplier is zero (P=1). Let us assume that a certain share of imports (s_o) with γ_d is associated with the domestic emission multiplier. Then, if we assume an increase in the share of domestically produced goods and services (a reduction of import shares), this should lead to increased emissions up to γ_A, γ_B or γ_C, depending on the selected straight line: A, B or C, respectively (see Figure 2). Model C can be considered inelastic in comparison to model A, whereas model B is more elastic than model A.

Fig. 2. Elasticity of emission multipliers with respect to shares (s) of imports



Coming back to Table 4, the resulting coefficients of determination for both models are 0.99, which is quite satisfactory. All estimated multipliers are significant at the 97% confidence level in the domestic model. In the total model, 18 are significant at the 99% confidence level, one at the 98% confidence level, another one at the 96% confidence level and the last one at the 93% confidence level. We have also addressed the impact of different levels of aggregation on the goodness of fit and the results of the model. As long as we aggregate products from a square supply-use system, the number of degrees of freedom should increase (e.g., up to 38, with 21 products and 59 industries). Therefore, the performance of R^2 should show us whether the goodness of fit of the model is really affected by aggregation. It is expected that for zero degrees of freedom, the R^2 will be exactly equal to 1. Consequently, because in our case the R^2 is sufficiently close to 1 (0.99) at the maximum level of aggregation, we can deduce that aggregation does not affect the goodness of fit of the model and did not affect the results.

Table 5 depicts the *P* ratio scores using the Leontief inverse-based emission multipliers. It is especially remarkable that its average value (0.09) is sensibly lower than that of the econometric approach (0.14). The same can be said using the median, which is by the way not affected by extreme values. In plain words, by using the Leontief inverse we would be underestimating the actual performance of the EU in reducing its carbon dioxide emissions via external trade. On average, the EU seems to be exporting more pollution than what one could expect from the Leontief inverse based approach. However, this rule does not hold for all industries individually. In the case of the EU, half were found to be underestimated and half overestimated.

Table 5.
Leontief inverse-based ratio of performance, *P*.
Source: Own elaboration

Code	Commodity	Leontief calculations Domestic model	Total model	*P*
01	Products of agriculture, hunting and related services	529.6	565.1	0.06
02	Fish and other fishing products; services incidental of fishing	1195.1	1246.5	0.04
03	Coal, uranium and other mining and quarrying products	1013.6	1067.8	0.05
04	Crude petroleum & natural gas; and incidental related services	547.4	563.7	0.03
05	Food products and beverages; Tobacco	462.3	511.2	0.10
06	Textiles, leather, wood, cork, pulp, paper and paper products	410.1	462.0	0.11
07	Coke, refined petroleum products and nuclear fuels	969.4	1213.1	0.20
08	Chemicals, rubber and plastics	622.4	708.8	0.12
09	Other non-metallic mineral products	1810.1	1869.6	0.03
10	Metallurgy and fabricated metal products	901.4	1000.9	0.10
11	Machinery and equipment; electrical machinery & apparatus	339.3	407.7	0.17
12	Office mach. & computers; radio, TV & communication equip. medical & precision intruments; transport equip.	328.6	420.9	0.22
13	Furniture; other manufactured goods; secondary raw materials	432.5	501.6	0.14
14	Electrical energy, gas, steam and hot water	4169.3	4241.7	0.02
15	Construction work	391.7	438.3	0.11
16	Trade; hotel and restaurant services	222.3	244.9	0.09
17	Land transport	721.1	752.3	0.04
18	Water transport	1263.4	1327.5	0.05
19	Air transport	1054.9	1119.2	0.06
20	Other services	147.8	163.9	0.10
21	Public Admin. Education and Health & social work services	164.9	182.8	0.10

Finally, we have carried out a macro check to test the robustness and coherence of the results by making a forecast of the total amount of direct domestic emissions (*C*) using the (total) econometric estimated model. The forecasted total amount of estimated direct emissions yielded 3,344.3 millions of tonnes of carbon dioxide, which is only 0.5% greater than the published total emissions (3,327.3 million tonnes). For the sake of clarification, this small deviation corresponds to the inherent errors of any econometric regression with a coefficient of determination lower than 1. Only if one has a perfect fit ($R^2 = 1$) then the deviation could have been reduced to null and actual estimations would have matched. Incidentally, this would correspond to equation (5), which is a deterministic system of equations with one single solution rather than an econometric equation.

7 Conclusions

This paper deals with the identification of appropriate measures of the performance of the EU in reducing its carbon dioxide emissions via external trade, both at the aggregate and at the industry levels. This issue falls under the EU Thematic Strategy on the Sustainable Use of Natural Resources (EU, 2004) which aims to de-couple environmental impacts associated with the use of natural resources from economic growth, in support of sustainable development.

We have found that standard measures based on the Leontief quantity model and profusely used by input-output practitioners and industrial ecologists will result in underestimation of the actual performance of the EU in reducing its carbon dioxide emissions via external trade. Briefly, standard measures currently available in the literature seem to assign the EU less amounts of exported air emissions (carbon dioxide). However, this rule does not hold for all industries individually. In the case of the EU, half were found to be underestimated and half overestimated. The most eco-efficient industries in transmitting emissions abroad by importing foreign products were crude petroleum and natural gas (04); coal, uranium and other mining and quarrying products (03); office machinery and computers (12); machinery and equipment (11); and chemicals, rubber and plastics (08). These results also show that domestic emission multipliers may vary according to different import shares, and that elasticities definitely play a key role in the capacity of an industry to reduce its emissions via external trade.

The output multipliers obtained using the Leontief inverse are positive and significantly biased, resulting from the assumption of a stochastic nature of either the technical coefficients or the elements of a transaction table (IOT). Needless to say, emission multipliers computed from biased output impact levels generate an even more serious overestimation of the emission impact. Consequently, this paper provides a new approach to estimating unbiased and statistically consistent emission multipliers. This approach has three important advantages: (a) it improves the accuracy of the environmental impacts assessed by industrial ecologists; (b) it finds a way to compute unbiased and consistent input-output multipliers for the IOA community; and (c) the use of the Leontief inverse is no longer necessary; only the supply and use matrices are required.

In addition, another advantage of this approach is that all the data needed to make the calculations are ready to use worldwide at many countries' National Statistical Institutes websites. Notice however that this paper deals particularly with the EU as a whole and benefited from the joint work developed by Eurostat and the Joint Research Centre's Institute for Prospective and Technological Studies of the European Commission for the compilation of the necessary EU aggregate data, which has already been partially published in Rueda-Cantuche, et al. (2009)

Acknowledgements

The author is extremely grateful to Peter Ritzmann and Jörg Beutel, for their support in the compilation of the supply-use and symmetric input-output tables for the aggregated European Union (2000).

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