The impact of renewable energy diffusion on European consumption-based emissions

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Abstract

The amount of carbon embedded in the final consumption of goods and services in a country or region depends on the amount of goods and services consumed and the emission intensity of the production processes along global production chains. A reduction of consumption-based emissions can be achieved from both sides, a reduction in total consumption and a reduction in the emission intensity of the production processes. EU consumption-based emissions are calculated using a combination of a multi-regional input-output (MRIO) system and a dynamic macro-economic input-output model, which is used to project the MRIO. The global diffusion of renewable energy technologies (PV and wind) can have a significant impact on the development of the EU28's consumption-based carbon emissions between 2010 and 2020. While the EU28s final demand continues to increase, emissions embedded in the goods and services consumed within the EU decrease in a global renewable energy diffusion scenario. This paper combines three different strands of literature, MRIO analysis, dynamic energy-economy-environment models and technological change in renewable energy, to model the impact of the global diffusion of renewable energies on European consumption-based emissions.

Highlights

- Global renewable energy technology diffusion is modelled using learning curves.
- Renewable energy technology diffusion has a large impact on emission intensity.
- EU consumption-based CO_2 emissions are calculated using multi-regional input-output analysis.
- Quantity and production technology matter for EU consumption-based CO_2 emissions.

Keywords

Consumption-based CO_2 emissions, renewable energy, technology diffusion

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Table of Contents

1 Introduction

Developing strategies and policies to influence consumption-based environmental impacts in general, and consumption-based carbon emission in particular, currently is on the agenda of policy makers. The amount of carbon embedded in the final consumption of goods and services in a country depends on the amount of goods and services consumed and the emission intensity of the production processes along global production chains. A reduction of consumption-based emissions can be achieved from both sides, a reduction in total consumption or a switch to less carbon incentive goods and a reduction in the emission intensity of the production processes. When for example[1] looking at the goods consumed in in the EU from the textiles, textile products, leather and footwear industry (short: textiles), we find that more than half of the embedded emissions occur in the electricity sector. In addition, in 2010, about three quarters of total carbon embedded in the final consumption of textiles in the EU was emitted outside EU. About 40% of carbon embedded in all goods and services consumed in the EU[2] can be traced back to the electricity sector, one third of this to countries outside the EU. Thus, if the electricity industry could provide entirely carbon free electricity, EU consumption-based emissions (excluding emissions from private road transport) could be reduced by 40%. In addition, the environmental impacts along global value chains would be lessened significantly.

Renewable power generation technologies, such as wind and solar photovoltaics (PV), but also concentrated solar power (CSP) or hydro, are deployed every year at an increasing scale globally. The share of these technologies used for electricity production directly influences the carbon intensity of the electricity industry. While the EU can directly influence the electricity mix within its territorial boundaries, influencing the electricity technology used abroad, which has a significant impact on EU consumption-based emissions, is more difficult. This lack of policy influence abroad is a general problem persisting with consumption-based policy approaches to climate mitigation. However, when following a pure cost approach, it could be argued that as soon as electricity production from renewable sources costs less than electricity production from fossil fuels (coal, gas, and oil), the switch from fossil fuels to renewables would follow automatically[3]. Based on this cost approach, it would therefore be sufficient to reduce the costs of renewable power generation technologies (RPGTs) to ensure that renewables will be deployed globally. Using the concept of learning curves from the literature on technological change, the cost reductions follow a learning process that depends on total capacity installed of the new technologies and possibly also active innovation activities such as RD&D investments. Thus, with increasing deployment of renewables within the EU as well as increasing RD&D efforts, the EU can achieve an accelerated costs decrease for these technologies, thus fostering deployment of RPGTs at a global scale through the effect of decreasing costs, and hence indirectly influencing the electricity mix abroad.

To calculate the effect of increasing RPGT deployment on consumption-based carbon emissions, this paper brings together three strands of literature, the literature on consumption-based carbon accounting based on multi-regional input-output analysis, the literature on dynamic energy-environment-economy models needed to project the MRIO system, and the literature on modelling renewable energy technology diffusion. The literature is summarized in Sections 2 and 3, which also introduce the models and data used for this exercise. Section 4 presents some results and Section 5 concludes.

[1] The examples given here are based on the author's own calculations and will be shown again in later sections of this paper.
[2] These calculations exclude residential emissions as well as emissions from private road transport, which are assumed to be 50% of total road transport. Tis will be explained in more detail in Section 2.3.
[3] This pure cost approach disregards technical problems of using only fluctuating renewable power sources.

2 Consumption-based carbon accounting

2.1 Multi-regional input-output analysis

The two major approaches for consumption-based carbon accounting are multi-regional input-output (MRIO) analysis, a top-down approach, and life cycle inventories (LCI), a bottom-up approach. Bullard et al. (1978), Treloar (1997), Suh and Huppes (2005), Feng et al. (2011), and Weinzettel et al. (2014) are some examples of literature comparing these two approaches. While life-cycle analysis is specific to certain products (also known as the carbon footprint of products), multi-regional input-output analysis is less detailed, but can be used to estimate consumption-based emissions at the country and industry level. When calculating consumption-based emissions for an entire country or region, here the EU, it therefore is useful to follow the MRIO approach, rather than the LCA approach where we would need to calculate the carbon footprint for millions of individual products.

Multi-regional input-output (MRIO) analysis uses input-output tables (showing demand for intermediate and final goods by industry) combined with bilateral trade data to allocate carbon emissions from producing to consuming countries. "For consumption-based accounting of greenhouse gas emissions in global carbon footprint analyses, MRIO has already become the norm" (Wiedmann et al., 2011b, p.1983). In recent years, several MRIO databases have been published; these include MRIOs based on GTAP (e.g. Peters et al., 2011a), EORA (Lenzen et al., 2012 & 2013), OECD (Nakano et al., 2009, Wiebe et al., 2012b), EXIOBASE (Tukker et al., 2009) and WIOD (Timmer et al., 2012) data.

The basic input-output model underlying the environmentally extended MRIO analysis is

$$x = Ax + y,$$

with x being the output (a vector in which each entry corresponds to one industry) that is necessary to satisfy all intermediate (Ax) and final demand (y). The matrix A is a square (industry $\times$ industry) matrix that displays the intermediate demand relations, i.e. the inter-industry requirements that are necessary to produce one good for each industry. This equation can be solved for x as

$$x = (I - A)^{-1}y.$$

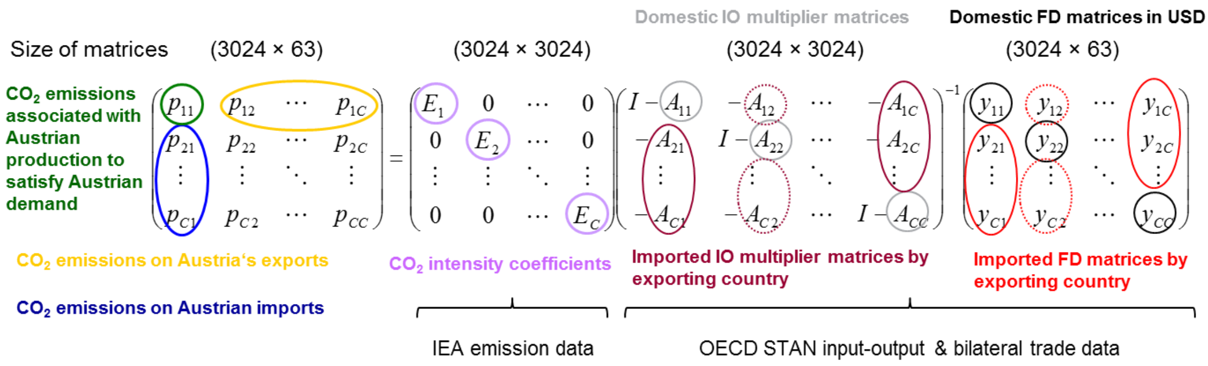
Using a diagonal matrix of emission intensities $\hat{e}$, it is possible to determine the emissions P that occur along the production chain for each final good consumed (in vector y):

$$P = \hat{e}(I - A)^{-1}y.$$

If for example, we want to know the emissions associated with one unit of final demand for goods from industry 1, the vector y would be 1 at the first position and 0 for all remaining industries. The resulting P would still have non-zero values in all positions because intermediate products from other industries are necessary to produce the final demand good of industry 1. To produce one t-shirt (textiles industry) for example you need the fabric (textiles industry), the color to dye the fabric (chemical sector) and the sewing machine including the needle (fabricated metal products) to sew the fabric. The fabricated metal products industry in turn needs the raw material for producing the needle from the basic metals industry. Also, for the use of the sewing machine, electricity is needs to be provided. During each of these steps carbon is emitted that can be allocated to the final good "t-shirt". Figure 1 shows the equation for multiple regions, with final demand y and intermediate input coefficients A for each country i (columns) broken down not only by industries, but also by country j of origin (rows): A_{ij} and y_{ij}. p_{ij} then is a vector (each entry corresponding to the industry in country

i) displaying the emissions that occur in the industry in country i while producing intermediate or final goods that are eventually consumed as final goods in country j.

Figure 1 Data used for MRIO system



$$\begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1C} \\ p_{21} & p_{22} & \cdots & p_{2C} \\ \vdots & \vdots & \ddots & \vdots \\ p_{C1} & p_{C2} & \cdots & p_{CC} \end{pmatrix} = \begin{pmatrix} E_1 & 0 & \cdots & 0 \\ 0 & E_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & E_C \end{pmatrix} \begin{pmatrix} I-A_{11} & -A_{12} & \cdots & -A_{1C} \\ -A_{21} & I-A_{22} & \cdots & -A_{2C} \\ \vdots & \vdots & \ddots & \vdots \\ -A_{C1} & -A_{C2} & \cdots & I-A_{CC} \end{pmatrix}^{-1} \begin{pmatrix} y_{11} & y_{12} & \cdots & y_{1C} \\ y_{21} & y_{22} & \cdots & y_{2C} \\ \vdots & \vdots & \ddots & \vdots \\ y_{C1} & y_{C2} & \cdots & y_{CC} \end{pmatrix}$$

Notes: 3024 = (63 countries x 48 industries). FD = Final Demand. IEA = International Energy Agency. OECD = Organization for Economic Cooperation and Development.

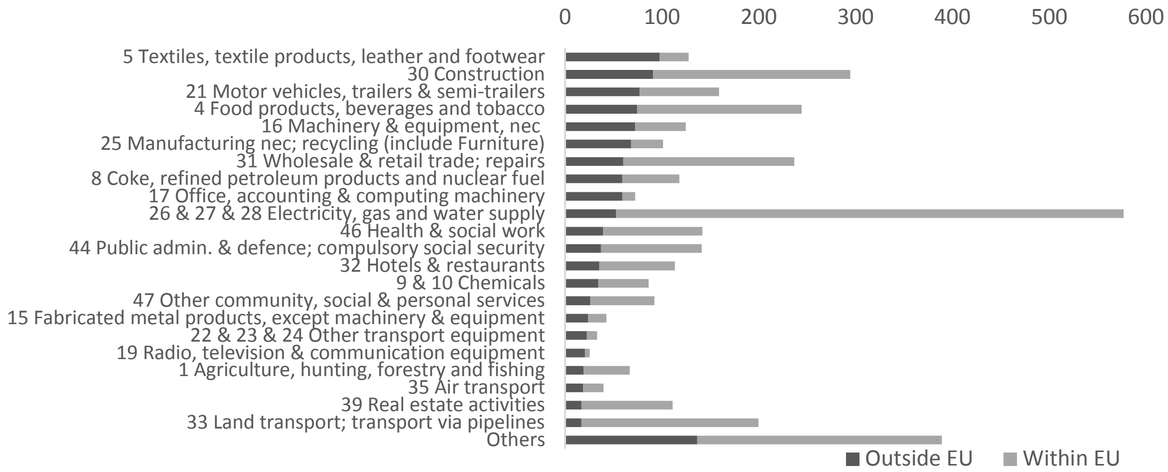
2.2 Multi-regional input-output database

The multi-regional input-output system used here is the Global Resource Accounting Model (GRAM), which is based on the OECD STAN input-output tables (IOTs), OECD STAN bilateral trade data for industries by end-use categories (BTDIxE) and the IEA energy and emission balances (IEA 2012a,b), as displayed in Figure 1. The equation uses common input-output notation with A being the inter-industry requirements matrix, y final demand vectors, and I the identity matrix. The environmental extension is displayed by matrices E_i for each country i consisting of the diagonalized vectors of emission intensities e, and the final result, the pollution matrix P consisting of vectors p_{ij} displaying the direct and indirect flows of emissions from country i to country$j$. The input-output tables cover 48 industries in ISIC Rev. 3 and are available for more than 50 countries. The remaining countries modelled in the system are based on national input-output tables or approximated using the structure of a similar country. Bilateral trade as well as emission data are available for all 62 countries plus the region rest of the world modelled in GRAM: EU28 countries, all non-EU OECD countries, BRICS (Brazil, Russia, India, China including Hong Kong and Taiwan, and South Africa), six emerging Asian economies part of the ASEAN trade agreement, Argentina, Chile, Israel, the Ukraine and six Middle-East North-African OPEC members. More details on GRAM can be found in Wiebe et al (2012 a, b).

2.3 EU28 consumption-based emissions

Figure 2 shows the emissions that occurred in 2010 along the global production chains to produce the final goods and services demanded from the industry displayed on the vertical axis. The graph distinguishes between emissions that occurred outside the EU – dark grey – and inside the EU – light grey. The industries are ordered according to the amount of emissions embedded in the products that were emitted outside the EU. Final demand for goods from the textile sector had the highest level of imported embedded emissions, followed by goods from the construction industry, motor vehicles and food products. All of these industries produce final goods for consumption, so that the absolute level of embedded emission is naturally higher than that from industries mainly producing intermediate goods, such as the iron and steel industry (not shown separately in the figure, but included in "Others"). Note that in the system we did not include emissions from private road transport, which are unquestionable the highest final consumption emissions. However, these emissions are direct final consumption emissions (not embodied in trade) and not influenced by the way in which electricity is produced in other countries, so that they were discarded from this specific analysis.

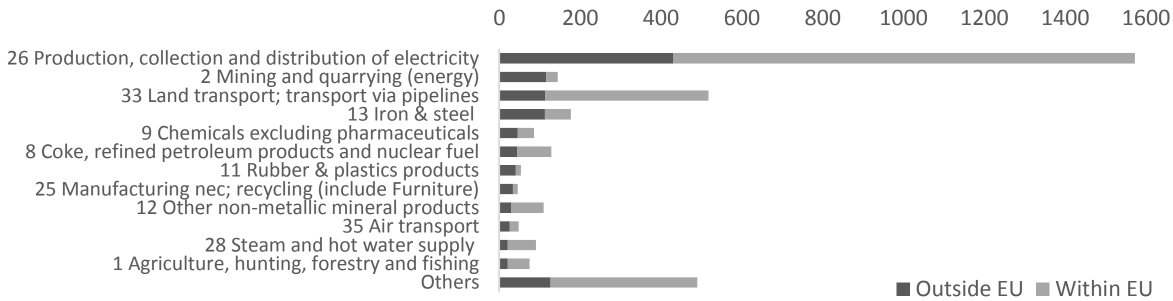
Figure 2 CO_2 emissions embodied in goods and services consumed in the EU28 for 2010 in MT CO2



Note: residential emissions and emissions from private road transport are omitted from this graph.

Figure 3, in contrast, shows the industries in which emissions occur during the production of goods and services that are eventually consumed in the EU28. The industries are ranked according to emissions produced outside the EU. The industry to which can be traced back more than 40% of total and more than one third of imported consumption-based emissions is production, collection and distribution of electricity (26). Ranked second is Mining and quarrying of energy resources (10% of imported, but only 4% of total consumption-based emissions), closely followed by Land transport (33) (10% of imported, 15% of total) and Iron and steel (13) (10% of imported, 5% of total).

Figure 3 Industries emitting CO_2 emissions embedded in goods consumed in the EU28 in 2010 in Mt CO_2 according to origin (emitted within EU28 or outside EU28)



Note: residential emissions and emissions from private road transport are omitted from this graph.

This graph clearly shows that the major source of emissions along global production chains is the electricity industry. Thus, for reducing not only territorial but also consumption-based emissions in the future, the importance of the diffusion of renewable power generation technologies worldwide is inevitable.

3 Renewable energy diffusion in an MRIO

To calculate the impact of global renewable energy diffusion, the static MRIO approach needs to be complemented with a dynamic model that is able to project the different components of the MRIO database: final demand, inter-industry and trade relations, as well as emission intensities taking into account the changing structure of the electricity industry.

3.1 Linking the MRIO with the dynamic 3-E model GINFORS_E

Calculating consumption-based emissions using the global MRIO approach has thus far almost exclusively been limited to historical analysis. There are two exceptions, Lutz and Wiebe (2012b), who have introduced a soft link between GRAM and GINFORS, and Wood (2014), who has used available forecasts of key data to project the EXIOBASE/CREEA database. The main limitation of using the MRIO approach to project consumption bases emissions is that it is strictly speaking a pure accounting system that can be used to reallocate production-based emissions along global supply chains to consumption, but that cannot be used to project the underlying database. Setting up an MRIO system for historical analysis is a very data intensive task and the exact same data is needed to apply the MRIO approach for estimating future consumption-based emissions. There are basically two options: first, directly projecting the consumption-based emissions indicators or, second, projecting the database that is used to populate the MRIO system. One way of simplifying the latter, is to first identify the most important system parts, i.e. those that influence the change in consumption-based emissions the most, and then concentrate on projecting these determinants. A method for this is for example structural decomposition analysis. Applying the average total decomposition technique developed by Dietzenbacher and Los (1998) showed that between 2000 and 2010 the effect of decreasing emission intensities was more than offset by increasing final demand and changes in the intermediate production structure. Unfortunately, from this three factor decomposition ($Y, A, \hat{e}$) it is not possible to distinguish between the impacts of trade changes and changes in total input coefficients. Still, a large-scale dynamic energy-economy-environment (3E) model is necessary that consistently projects the economic development on the industry level as well as corresponding demand for different energy carriers and related production-based emissions into the future. This dynamic simulation model should be based on the same database as the MRIO model, thus using the same sectoral and regional aggregation for the underlying input-output, bilateral trade, energy and emissions data.

GINFORS_E is a version of the GINFORS (Global INterindustry FORecasting System) model (see Appendix) tailored to fit the MRIO GRAM. It is based on the exact same historical database as GRAM (OECD input-output tables and bilateral trade data as well as IEA energy balances), and thus covers the exact same industries (48 industries in ISIC Rev. 3 classifications) and countries. Those countries, for which no input-output tables exist, are represented in GINFORS_E by simple macro-economic models projecting the main components of GDP as well as the key labor market indicators. Therefore, for these countries we also have the same information available in the projections as we had for the historical analysis. One exception is the rest of the world, for which sufficient information to construct a simple macro-economic model is not available. Therefore, we assume that both trade shares as well as emission intensities are constant. Hence, the numbers for the rest of the world should be interpreted with caution. The main components needed for the MRIO system (input-output tables, trade shares, emission data) are derived in GINFORS_E as follows:

For each country dynamic macro-economic models project core macro-economic indicators such as aggregated final demand components, price level as well as labor market aggregates (employment, wage), see Wolter et al. (2014) for details. The country-specific models are linked via international trade. The country models provide the demand for total import goods and the prices for export goods[4]. The trade model estimates trade shares for the biggest 999 bilateral trade flows[5] of goods in

[4] Data for export prices at the industry/goods level (industries/goods are classified in ISIC Rev. 3. The underlying assumption for using trade data in goods and input-output data at industry level is that each industry only produces its own goods. This assumption could be refined with using supply-and-use tables.) are assumed to be same as production prices. If available, production prices are taken from the OECD STAN database. For the remaining countries historic times series for production prices at the industry level were

2010 at the level of goods depending on relative prices and time trends. The remaining trade shares are scaled accordingly. The trade shares are import shares for each good for all countries from all other countries. The growth rate of total import demand determines the growth rates of import demand at the goods level. This assumption could be refined when having a more detailed determination of the final demand for goods and services (see next paragraph). Using the import shares, the import demand of all countries is allocated to exporting countries, thus determining their exports at the goods level. Gross exports are then calculated by the sum over all goods.

The country-specific input-output model is populated using the macro-economic variables following a top-down approach to estimate the variables at the industry level based on their macro-aggregates. While the aggregates of the final demand components change individually (household consumption, government consumption, gross fixed capital formation), the industry breakdown remains constant. Modelling the demand for goods from different industries individually can improve the overall results of this modelling exercise. Input-coefficients in the input-output country models are assumed to remain constant[6] except those that are changed by the changes in the energy mix used in the economy. Based on the energy balance, which displays which energy carrier is used by which industry, the coefficients of four industries in all other industries are changed: coal and crude oil inputs (industry 2 mining and quarrying – energy), coke refined petroleum products and nuclear fuels (industry 8), collection, generation and distribution of electricity (industry 26) and manufacture of gas and distribution of gaseous fuels through mains (industry 27). The changes are based on the changes in the use of each energy carrier in each industry, which in turn depends on production and relative energy prices. Carbon emissions on the industry level are calculated from the energy balance using constant (2010) emission factors for each energy carrier. Production and value added calculated using the Leontief production function. The model is solved iteratively each year to ensure internal consistency.

3.2 Renewable power generation technology diffusion

The representation of technological change in economic models depends on the type of model used. In theoretical endogenous growth models (Aghion and Howitt, 1997), technological change enters the model through a (exogenous) parameter in the production function. In evolutionary growth models, technological change can be modeled endogenously using the heterogeneity of agents, which induces the motivation for changing products or behavior to catch up with or differentiate from others. Technological change is then modeled as innovation and selection processes. In input-output models, the technological structure is included in the intermediate input coefficient matrix. Technological changes are represented by changes of the corresponding coefficients.

Input-output tables display the intermediate demand relations between the different industries and service sectors of an economy. Models that are based on input-output data therefore represent the technological structure of the economy through the input coefficients calculated from the input-output tables. Innovation and technological change at the industry level is represented by changes in the coefficients. The coefficients, however, are not independent. Sonis and Hewings (2009) present an analytical approach to analyze the ``spread of the Schumpetarian wave within the Leontief inverse of input-output systems''.

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constructed based on the general price level, wage development and energy prices, all weighted with their respective input-coefficients from the input-output table. The projection of the price development at the industry level uses the same approach.

[5] Choosing the biggest 1000 or more trade flows was not possible because of software limitations regarding the automated procedure for the econometric equations and there inclusion in the model.

[6] The actual idea is that real input coefficients remain constant, while nominal input coefficients change with changing prices at the industry level. This has not yet been implemented in the model.

Pan and Köhler (2007) bring together the modeling of endogenous technological change in energy systems using learning curves and logistic curves with the change in the input-output coefficients. Using the example of the British wind power industry they show how future costs, prices and installed capacity are estimated using learning and logistic curves. The curves can then be used to adjust the input coefficients. In case of a one-factor (capital) learning curve the input coefficients for new technical processes are changing according to Pan and Köhler (2007, p. 755):

$$a_{ijt}^{N} = a_{ijt}^{0}\left[\sum\nolimits_{t} K(t)\right]^{-b}$$

where K(t) is the capital endowment at time t and b>0 is the learning rate. If technological progress is modeled with a logistic curve, the input coefficients are determined by

$$a_{ijt}^{N} = a_{ijt}^{0}\left[\alpha_l + \frac{\alpha_u}{\left(1+\theta\exp\left(-\beta\left(t(1+G)-\frac{\pi}{1+G}\right)\right)^{1/\theta}\right)}\right]^{-b}$$

The logistic function includes more parameters that need to be calibrated than the learning curve. 0<α_l<α_u<1 are efficiency parameters of the new technology at the final stage and the initial stage compared to the original efficiency level, i.e. the final technology at saturation level is assumed to be $1/\alpha_l$ times more efficient than the original technology. θ is an asymmetry parameter of the growth process, a θ =1 represents symmetrical growth. β, the average growth rate, is multiplied by two factors that are composed of time *t*, the growth rate of R\&D investment *G* and the time of maximum growth π. If information regarding the parameters is readily available for the technology, the logistic function seems to be a better approximation of the underlying technological change than simple one-factor or two-factor learning curves Pan and Köhler (2007).

The weighted average of old (a_{ijt}^{0}) and new (a_{ijt}^{N}) technical coefficients gives the total input coefficient a_{ijt}. Faber et al. (2007, p.25) stress the importance of noting that the coefficients are averages within aggregate industrial sectors; therefore, they do not necessarily represent the technology of individual enterprises. Bullard and Sebald (1977) analyze the effect of changes in energy technologies using an input-output model. As there is only one aggregate energy sector in the input-output data, they split this single energy sector of the input-output matrix into several energy service sectors. We use a combination of these approaches as will be shown below.

The deployment and cost development of renewable power generation technologies are modelled using learning curves. The technologies selected for this analysis are PV and wind, as these have been deployed on a global scale for more than 20 years and, thus, sufficient data for the approach used here is available. The modelling is based on global two-factor learning curves for the development of global average PV module and wind turbine costs. The data for global capacity and world average prices per MW are taken from Bloomberg (2013) and those for RD&D from OECD & IEA (2013a). The results are slightly more conservative (lower than average learning rates) than other learning rate estimates in the literature as e.g. surveyed by Kahouli-Brahmi (2008), who analyzed 77 learning-by-doing and 17 learning-by-(re)searching rates estimated in different energy-environment-economy models between 1974 and 2007. Capacity addition in each country (calculated from data on capacity installed from OECD & IEA, 2013b) is estimated based on global average prices. The countries covered here are displayed in Table 2 in Appendix 2; these countries are those that currently have some installations of PV and Wind[7]. In addition, capacity additions may depend on a logistic expression considering the share of renewables in total electricity consumption or time, so that instead of an exponential increase in PV and wind capacity installed, capacity installations follow the s-curve of technology diffusion as for example suggested by Rogers (1962). The development of PV and wind capacity installed is displayed in Figure 4 and Figure 5. The difference between the world total in our model (solid black line) and the Bloomberg projection (World BB – dashed black line) is that we do not have data for all countries.

Figure 4 Global wind power capacity installed by country in GW

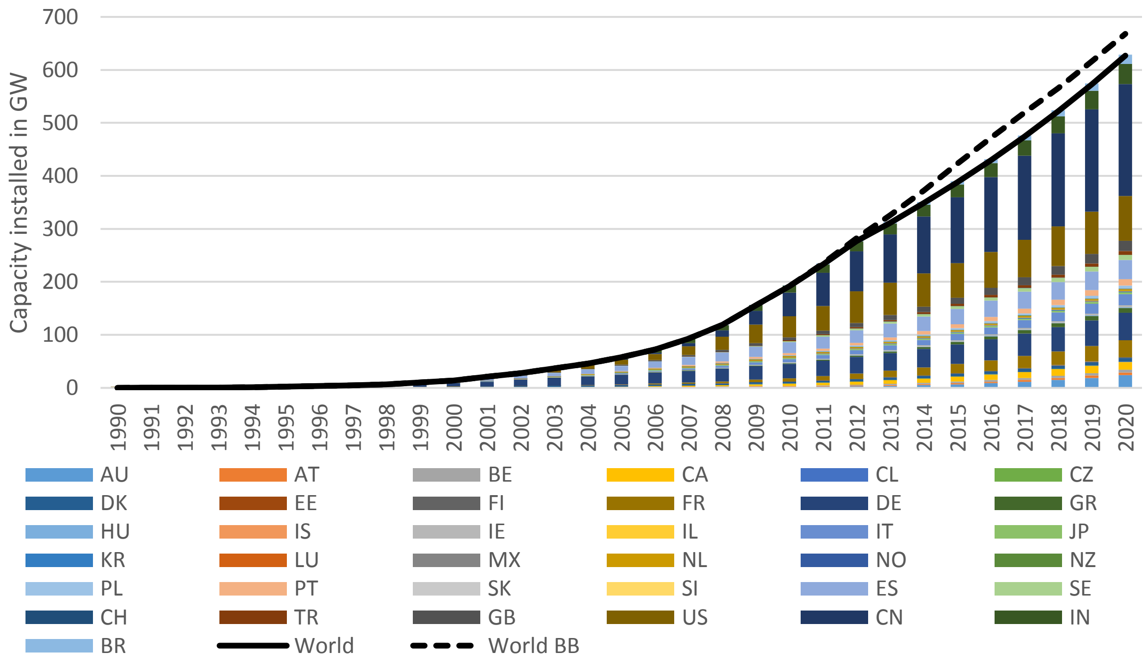
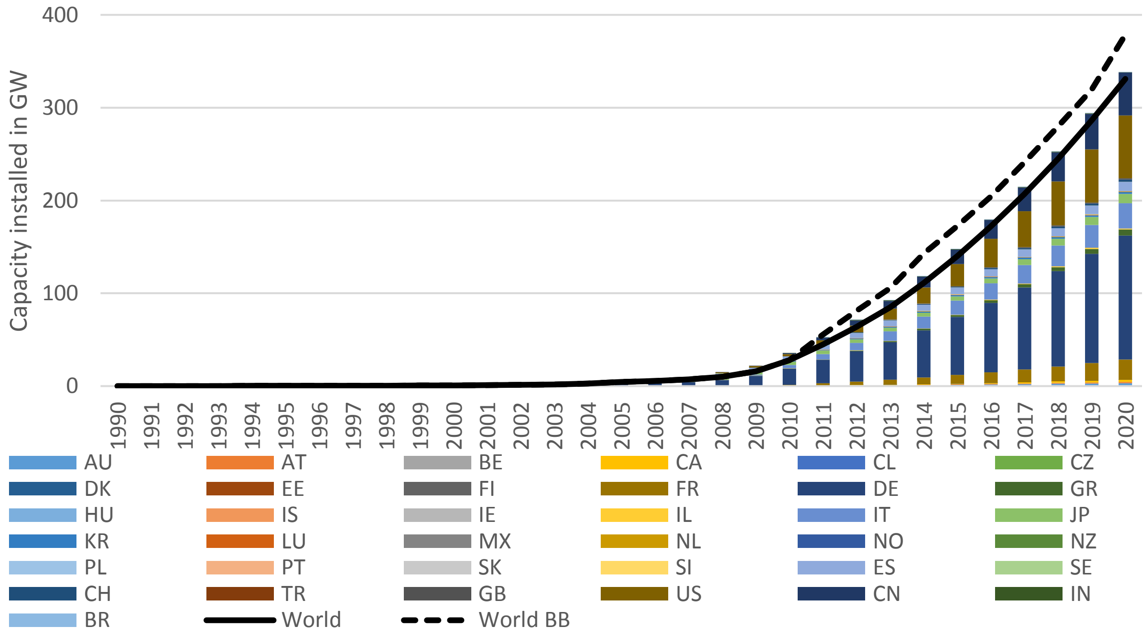


Figure 5 Global photovoltaic power capacity installed by country in GW



[7] This analysis lacks the incorporation of projects currently planned or under construction in countries other than those covered by the OECD & IEA (2013b) data. If more countries were covered, global installations would increase even faster, thus accelerating the cost decrease and increasing the overall effects.

The feedback into the previously existing model of the energy industry in GINFORS_E requires changes in two different model parts: First, in the energy balance (1), where the electricity mix is determined, and, second, in the input coefficients in the input-output model as the electricity industry itself uses PV and wind technology as inputs rather than fossil fuels (2a) and PV and wind technologies are produced differently from fossil fuel power plants (2b).

(1) Given the priority feed-in for renewables, which is set by policy in most countries, e.g. in the German Renewable Energy Sources Act, the inclusion of renewables into the existing energy balance is straight forward. Given total electricity demand, which is determined endogenously in the model, and capacity installed of PV and wind multiplied with constant full load hour factors, as well as exogenously determined electricity generation from hydro and nuclear power stations, the amount of electricity needed from coal and gas fired power stations is calculated as a residual from total electricity demand.

(2a) For the electricity industry (industry 26), the decrease in the input coefficients from fossil fuel use (industries 2, 8, 27) is accompanied by an increase in the coefficients from industries "16 machinery and equipment", which produces wind power plants, and "18 electrical machinery and apparatus", which produces PV systems. The total increase in the coefficients of 16 and 18 is the sum of the decrease in the coefficients of 2, 8, and 27. The total increase is distributed among 16 and 18 according to the share of capacity additions of wind (16) and PV (18) in total capacity additions of wind and PV multiplied with their respective global average costs per MW.

(2b) The use of PV and wind technologies by the electricity industry was described in (2a), but the technologies also need to be produced. As mentioned above, wind technologies are produced in industry "16 machinery and equipment" and PV technologies are produced in industry "18 electrical machinery and apparatus". Thus, with increasing wind and PV technology production, the input coefficients of these industries change. As neither PV nor wind technologies are produced in every country modelled in GINFORS_E and GRAM, these input coefficients are only changed for selected producing countries listed in Table 1. To do this, the share of wind/PV technology output in total output of industries 16 and 18 for the year 2009 (the last year for which historical data of the input-output models is available) is required. These numbers are calculated from PV/Wind technology production in MW per country (based on global additional capacity installed distributed across countries based on the shares presented in Table 1) multiplied by global average price and then divided by the output of the respective industries from the input-output tables. This share together with the input coefficient vector for PV and wind technologies from (Lehr et al., 2011), can be used to split the input coefficient vector for 16 and 18 for 2010. Thus, splitting the industries into two as Bullard and Sebald (1977) have done for the energy industry: one input vector for the original industry without the renewable power generation technology and one input vector for the renewable power generation technology. For the projections, the share of wind/PV to total output of industries 16 and 18 is used to determine the weight for the two parts of each of the vectors (one part is 16 without wind and one part is wind, and the same for 18: one part is 18 without PV and one part is PV), so that the total input coefficient vectors for 16 and 18 can be calculated. In contrast to Pan and Köhler (2009) where the coefficients are changed through learning curves, here, it is the share of PV/wind technology in their respective industry that drives the total coefficient change. The share, however, depends on the development of the PV/wind deployment, which is modelled using learning and logistic curves. The model is solved iteratively, i.e. using multiple iterations in each year. The assumption for the first iteration is that the shares are those from the previous year. The output related to wind and PV changes with global capacity additions and the industry totals with the common input-output model. Thus, the new shares of the parts in total industry output can be calculated in each iteration, in turn influencing total output of the industries in the next iteration.

Table 1: Country shares in PV module production and Wind turbine production[8]

PV module production shares (2010)		Wind turbine production shares (2009)	
China	53%	**Denmark**	19%
Japan	12%	**U.S.**	12%
Germany	13%	**China**	25%
US	7%	**Germany**	15%
Korea	5%	**Spain**	7%
Spain	4%	**India**	10%
Italy	2%	**Netherlands**	4%
Mexico	1%		
Sweden	1%		
Austria	1%		

4 What is the impact of renewable power generation technology diffusion on consumption-based carbon emissions in the EU?

To analyze the effect of global PV and wind technology diffusion on EU consumption-based emissions, the MRIO system was applied to different combinations of the input data, see Figure 6:

1) using data for 2000 for final demand, input structure and emission intensities (2000);
2) using data for 2010 for final demand, input structure and emission intensities (2010);
3) using data for 2020 for final demand, input structure and emission intensities projected with GINFORS_E for global renewable energy diffusion (2020 RE diffusion);
4) using data for final demand from 2010 and for the technology (input structure and emission intensity) from 2020 (2020 technology and 2010 final demand); and
5) using data for final demand from 2020 and for the technology (input structure and emission intensity) from 2010 (2010 technology and 2020 final demand).

The first two bars in Figure 6, i.e. 1) and 2) of the above bullet points, are based on historical data. The third bar represents the result of projecting final demand, input structure and emissions intensity considering the diffusion of PV and wind with the GINFORS_E model. The latter two calculations, i.e. 4) and 5) of the above bullet points, were performed to show the impact of RE diffusion given final demand on consumption-based emissions, that is

4) What would be the level of EU consumption-based emissions in 2010 if the technology of 2020, i.e. high penetration of PV and wind, was used?

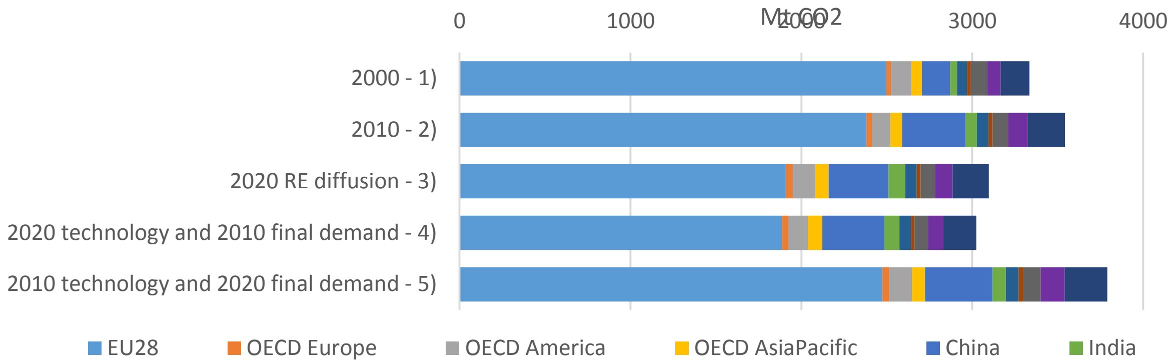
5) What would be the level of EU consumption-based emissions in 2020 if the "current" 2010 technology was used?

[8] Own estimations based on (IEA PVPS 2011 figure 6, 2014 figure 14) for PV modules and for wind turbines on https://www.rolandberger.com/media/pdf/Roland_Berger_Wind_Turbine_Manufacturing_20111128.pdf, http://www.reuters.com/article/2010/03/29/us-windenergy-market-consultant-idUSTRE62S12620100329 and http://www.nawindpower.com/e107_plugins/content/content.php?content.12710

Figure 6 shows that total emissions embedded in EU final demand (EU consumption-based emissions) increased between 2000 and 2010. While emissions originating from Europe (light blue) decreased, emissions originating from China (blue), India (light green), the Middle-East and North-African OPEC members (MENA-OPEC, purple) and the rest of the world (RoW, dark blue) increased. The decrease in emissions originating from EU28 territory was due to a steady decrease in emission intensities, especially through an increase in the share of renewables in electricity production. As this share is expected to increase in the future, absolute emission levels are projected to further decrease as shown by the bar “2020 RE diffusion”. However, the big decrease in EU28 territorial emissions that occur along production chains for final goods and services consumed in the EU28 is not only due to emission intensity improvements, but also due to an increasing fragmentation of global production chain, so that the import content (share of imports embedded in the final good) of final goods and services consumed in the EU increases. The production technologies, i.e. emission intensities of production in almost all regions are more carbon intensive than those used within the EU (Figure 7). The only region with lower emissions per dollar of production is the region including the remaining European OECD countries. China for example emits four times as much CO2 per dollar of production and India six times as much as the EU28, but the MENA-OPEC countries have by far the highest emission intensity of production, more than ten times the EU28 level. However, these are expected to be significantly improved until 2020.

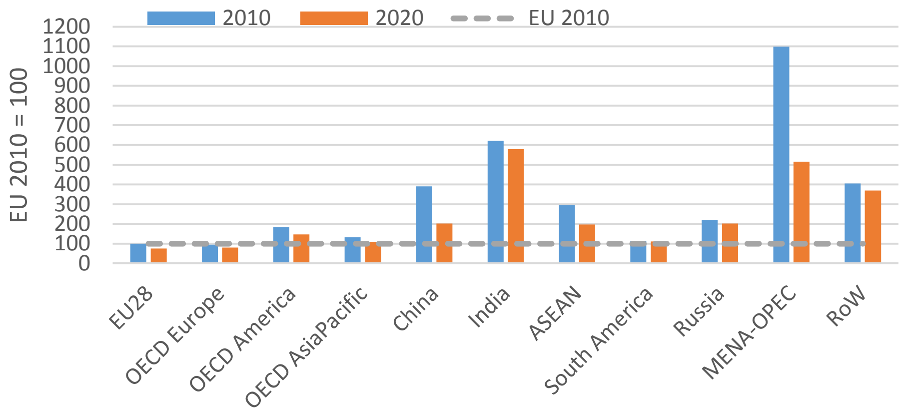
When comparing bar 2) with 4) and 3) with 5), which have the same amount of underlying EU final demand respectively, but different technologies (input coefficients and emission intensity), it becomes clear that the technology plays a significant role in determining the total amount of embedded emissions. For the 2010 level of final demand (2 and 4), consumption-based emissions are 15% lower when the 2020 technology with highly diffused renewable energy is used. For the 2020 level of final demand (3 and 5), consumption-based emissions are almost 20% lower with the 2020 technology than what they could be if the technology would not change over the coming years, but remain the same as it was in 2010. In turn, when comparing the same technology with changing level of final demand, we find that with the higher final demand in 2020, total embedded emissions would be 7% higher than in 2010, when using the 2010 technology (comparison of 5 and 2) and 2.5% higher in 2020 compared to 2010, if in both years 2020 technology was used (comparison of 3 and 4). The corresponding changes can also be analyzed using total average decomposition (Dietzenbacher and Los, 1998). The virtue is that not only the composition of the total change is visualized, but also that uncertainty intervals can be given. The analysis, with base year 2000, is displayed in Figure 8. The numbering of the bars is the same as for Figure 6. The analysis shows that between 2000 and 2010, the increase in emissions due to an increase in final demand (blue part of the bar) are completely offset by decreasing emissions from improvements in emission intensity along global production chains (green part). The total change is approximately the same as the average change due to changes in the global input coefficients, which entail changes in the input coefficients and changes in intermediate trade shares. The error lines associated with each component display the minimum and maximum values of the decomposition analysis, which deviate about 50% from the average value. For the three scenarios the base year is again 2000. For the renewable energy diffusion scenario (3), decreasing emissions from improvements in energy intensity along global production chains are able to offset both, increasing emissions from increasing final demand and increasing emissions from changes in the global input coefficients. Interestingly, the technology impact when only looking at emission intensity would be even greater, if we did not include the change in the production technology A. It would be desirable to decompose the change in the global A matrix into changes in the input coefficients and changes in import shares. A decomposition technique that is able to do that is currently developed by Hoekstra et al. (2014), but was not yet available for the analysis at hand.

Figure 6 Origin of emissions embedded in EU28 final demand



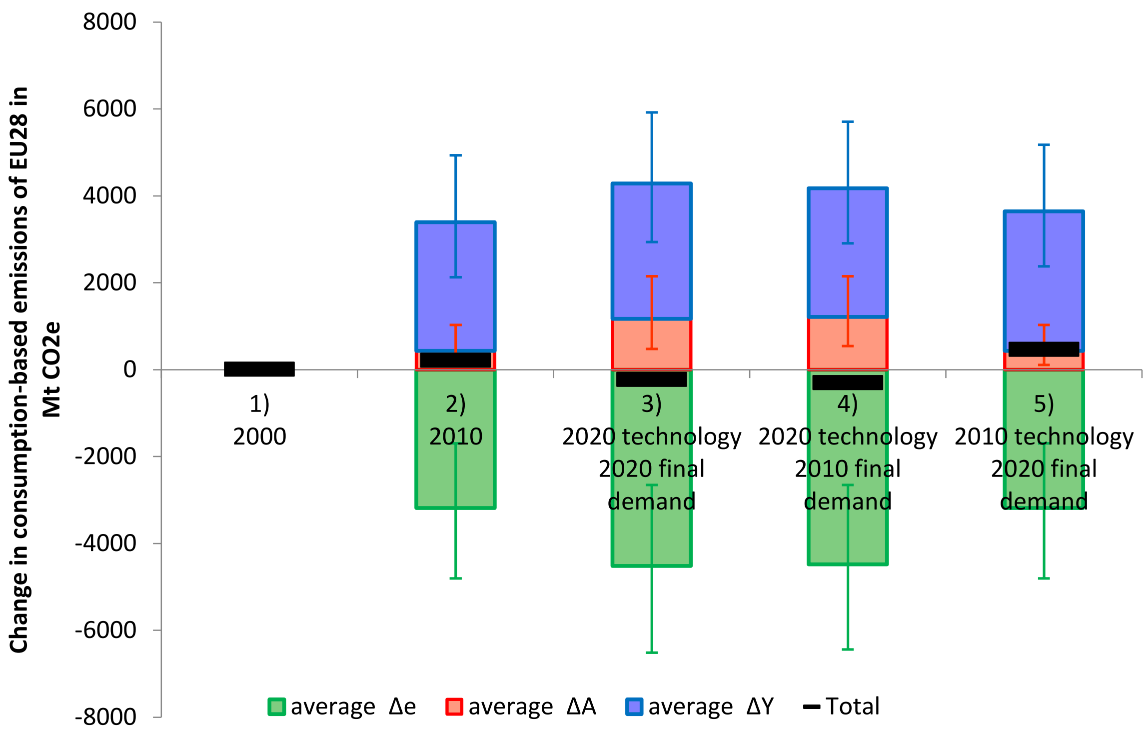
Note: residential emissions and emissions from private road transport are omitted from this graph.

Figure 7 Emission intensity of production (EU28 2010 =100)



Note: residential emissions and emissions from private road transport are omitted from this graph.

Figure 8 Decomposition of changes in EU28 consumption based emissions



Note: residential emissions and emissions from private road transport are omitted from this graph.

For scenarios 4 (2020 technology and 2010 final demand) and 5 (2010 technology and 2020 final demand), we see that the size of the bars is the same as for 2 and 3: the size of the blue bar in 4 is the same in 4 and 2 (both 2010 final demand) as well as in 3 and 5 (2020 final demand). And the size of the green and orange bars are the same for 2 and 5 (both 2010 technology) and for 3 and 4 (both 2020 technology). Overall, the total change in consumption-based emissions is dominated by changes in the technology, while the change in consumption based emissions due to changes in the level of final demand is rather low.

5 Discussion and concluding remarks

As has been shown by the historical analysis of consumption-based carbon accounts, a big share of the emissions embedded in the goods and services consumed within the EU is emitted during electricity production for various processes along the production chain, not only within the EU, but also outside the EU. While the EU itself has a number of policies in place to decarbonize the electricity sector, it hardly has any direct influence on the electricity mix abroad. However, given that renewable power generation technologies are employed on an increasing scale the more the costs of these technologies decrease, and that the costs decrease with increasing capacity installations (learning curves), the EU can indirectly influence capacity installations elsewhere in the world by increasing deployment of renewable power generation technologies within the EU. It can also be argued that domestic RES policies and deployment deliver extra benefits of lower emissions abroad via global learning curves, which in turn also reduce EU consumption-based emissions. To estimate the impacts of the diffusion of renewable energy on European consumption-based carbon emissions, three theoretical approaches had to be combined: a global multi-regional input output needs to be consistently projected into the future using a dynamic energy-economy-environment-model, that additionally takes into account the effects of technological change following the deployment of solar PV and wind electricity technologies.

Projecting an MRIO system is a complex task. GINFORS_E consistently projects the level of final demand for all countries as well as the energy mix and, thus, the emission intensity of production. Changes in the 999 largest bilateral trade flows on the goods level are estimated as well. It is only the sectoral composition of final demand and total input coefficients that remained constant when projecting the entire MRIO structure. An exception are coefficients and final demand of the energy-related industries, which are the most important when analysing possible effects of a changing structure on consumption-based emissions. If we were to analyse for example value added in trade, we would need to focus on other industries and refine their modelling. For better determining which components of the total MRIO system are important for the estimation of consumption-based indicators, be it emissions, resource use, value added, or employment, developing an extended structural decomposition approach, that is able to distinguish between the effects of different parts of the system, not only the total matrices, is desirable. A methodology decomposing the important trade partners is currently being developed by Hoekstra et al. (2014).

The results of the scenario analysis here show that both quantity of final demand as well as the technologies (emission intensity and input coefficients) used along global production chain matter for the level of consumption-based carbon emissions. With globally increasing capacity installed of wind power and PV, EU consumption-based emissions decrease, while consumption itself in nominal terms continues to increase. When looking at the differences between the scenarios in greater detail it becomes clear that differences in the technology (higher share of PV and wind in electricity production) have a higher contribution (-15% and -20%) to consumption-based emissions than differences in final demand (+7%, +2.5%).

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Appendix 1 – Philosophy of GINFORS_E

The global INFORUM type model GINFORS_E (Global INterindustry FORecasting System - Energy) describes the economic development, energy demand, CO2 emissions and resource inputs for more than 50 countries and one region, 48 industries/product groups, 20 energy carriers and 9 resources. The explicitly modeled countries cover about 95% of world GDP and 95% of global CO2 emissions. The aggregated region "Rest of the World" is needed for the closure of the system. The model is documented in Lutz et al. (2010). Current applications of the model can be found in Barker et al. (2011a), Giljum et al. (2008), Lutz and Meyer (2009a, 2009b), Lutz and Wiebe (2012a) and Lutz (2010).

GINFORS is in many respects close to neoclassical CGE models, but shows some major differences. The most important difference is the non-equilibrium assumption. The model is solved in every year until it converges and is not optimized over some specific time horizon. Another difference is the representation of prices, which are determined due to the mark-up hypothesis by unit costs and not specified as long run competitive prices. But this does not mean that the model is demand side driven, as the use of input-output models might suggest. Even though demand determines production, all demand variables depend on relative prices that are given by unit costs of the firms using the mark-up hypothesis, which is typical for oligopolistic markets. Firms are setting the prices depending on their costs and on the prices of competing imports. Demand is reacting to price signals and thus determining production. Hence, the modeling in GINFORS includes both demand and supply elements.

All behavioral parameters of the model are estimated econometrically, and different specifications of the functions are tested against each other, which gives the model an empirical validation. An additional confirmation of the model structure as a whole is given by the convergence property of the solution which has to be fulfilled on a yearly basis. The econometric estimations build on times series from OECD, UN and IEA from 1990 to 2011. However, for a number of variables the data were only available for a shorter time period. The modeling philosophy of GINFORS is close to that of INFORUM type modeling (Almon 1991) and to that of the model E3ME from Cambridge Econometrics. Common properties and minor differences between E3ME and GINFORS are discussed in Barker et al (2011b).

Appendix 2 – Country coverage of RPGT modelling

Table 2: Country coverage of of OECD & IEA (2013b) Net capacity of renewables

Australia	Hungary	Poland
Austria	Iceland	Portugal
Belgium	Ireland	Slovak Republic
Canada	Israel	Slovenia
Chile	Italy	Spain
Czech Republic	Japan	Sweden
Denmark	Korea	Switzerland
Estonia	Luxembourg	Turkey
Finland	Mexico	United Kingdom
France	Netherlands	United States
Germany	Norway	
Greece	New Zealand	
Brazil*[1]	China*[2]	India*

**Global Wind Reports, GWEC Global Wind Energy Council*

[1] *EPIA - Global Market Outlook for Photovoltaics until 2016*

[2] *http://www.epia.org/fileadmin/user_upload/Publications/GMO_2013_-_Final_PDF.pdf*

Appendix 3 – Industry coverage of GRAM and GINFORS_E

Table 3: Industry classification of OECD STAN input-output tables (ISIC Rev. 3)

1 Agriculture, hunting, forestry and fishing	25 Manufacturing nec; recycling (include Furniture)
2 Mining and quarrying (energy)	26 Production, collection and distribution of electricity
3 Mining and quarrying (non-energy)	27 Manufacture of gas; distribution of gaseous fuels through mains
4 Food products, beverages and tobacco	28 Steam and hot water supply
5 Textiles, textile products, leather and footwear	29 Collection, purification and distribution of water
6 Wood and products of wood and cork	30 Construction
7 Pulp, paper, paper products, printing and publishing	31 Wholesale & retail trade; repairs
8 Coke, refined petroleum products and nuclear fuel	32 Hotels & restaurants
9 Chemicals excluding pharmaceuticals	33 Land transport; transport via pipelines
10 Pharmaceuticals	34 Water transport
11 Rubber & plastics products	35 Air transport
12 Other non-metallic mineral products	36 Supporting and auxiliary transport activities; activities of travel agencies
13 Iron & steel	37 Post & telecommunications
14 Non-ferrous metals	38 Finance & insurance
15 Fabricated metal products, except machinery & equipment	39 Real estate activities
16 Machinery & equipment, nec	40 Renting of machinery & equipment
17 Office, accounting & computing machinery	41 Computer & related activities
18 Electrical machinery & apparatus, nec	42 Research & development
19 Radio, television & communication equipment	43 Other Business Activities
20 Medical, precision & optical instruments	44 Public admin. & defence; compulsory social security
21 Motor vehicles, trailers & semi-trailers	45 Education
22 Building & repairing of ships & boats	46 Health & social work
23 Aircraft & spacecraft	47 Other community, social & personal services
24 Railroad equipment & transport equip nec.	48 Private households with employed persons & extra-territorial organisations & bodies