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Factoring in the forgotten role of renewables in CO_2 emission trends using decomposition analysis

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ABSTRACT

This paper introduces an approach for separately quantifying the contributions from renewables in decomposition analysis. So far, decomposition analyses of the drivers of national CO_2 emissions have typically considered the combined energy mix as an explanatory factor without an explicit consideration or separation of renewables. As the cost of renewables continues to decrease, it becomes increasingly relevant to track their role in CO_2 emission trends. Index decomposition analysis, in particular, provides a simple approach for doing so using publicly available data. We look to the U.S. as a case study, highlighting differences with the more detailed but also more complex structural decomposition analysis. Between 2007 and 2013, U.S. CO_2 emissions decreased by around 10%—a decline not seen since the oil crisis of 1979. Prior analyses have identified the shale gas boom and the economic recession as the main explanatory factors. However, by decomposing the fuel mix effect, we conclude that renewables played an equally important role as natural gas in reducing CO_2 emissions between 2007 and 2013: renewables decreased total emissions by 2.3–3.3%, roughly matching the 2.5–3.6% contribution from the shift to natural gas, compared with 0.6–1.5% for nuclear energy.

1. Introduction

Over the period of 1990–2007, U.S. energy-related CO_2 emissions showed an increasing trend and were projected to continue increasing (EIA, 2007). In 2007, however, emissions instead took a sharp turn downwards and by 2013, annual CO_2 emissions had decreased by 10% (600 million tonnes). Over the same period, renewable energy increased significantly. Most of the expansion in renewables came from wind energy, which increased from 0.36 exajoules (EJ) to 1.69 EJ (on a primary energy basis) over the period. There was also an increase of roughly equal magnitude in bioenergy consumption from 3.68 EJ to 4.93 EJ. The increase in solar energy was modest in absolute terms (from 0.069 EJ to 0.24 EJ), though significant in relative terms, with more than a threefold increase in six years (EIA, 2016). This increase in renewable energy was matched by a similarly unprecedented decline in costs (Wagner et al., 2015). Observing such trends, we want to be able to answer the question: what was the contribution from renewables to U.S. CO_2 emissions reductions?

Decomposition analysis provides a method for addressing that question. As Wang et al.'s (2017) review shows, index decomposition analysis (IDA) and structural decomposition analysis (SDA) are techniques that have been extensively used by researchers to analyze drivers of changes in energy-related emissions for energy and climate policy assessment. IDA in particular has proven useful for tracking improvements in economy-wide energy efficiency: as noted by Wang et al. (2017), the activity intensity effect, which captures changes in energy efficiency as part of the IDA, is used by energy agencies in numerous countries, including the U.S., Canada, Australia, New Zealand, and Europe (Belzer, 2014; OEE, 2013; Stanwix et al., 2015; Elliot et al., 2016; ODYSSEE, 2015). Similarly, we here demonstrate how IDA can be used to track the role of renewables in CO_2 emission trends by separately quantifying the impacts of renewables, nuclear energy, and natural gas.

We complement our IDA with an SDA for the same period. By doing so, we can compare differences between these two methods. We assess, in particular, whether it is legitimate to use the much simpler IDA to address the question of renewables' contribution or whether the complex SDA is needed. We find that IDA is adequate to address this question.

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Furthermore, applying both IDA and SDA to the same case study provides new insights on the drivers behind recent U.S. CO_2 emission reductions with potentially important implications for policy. Specifically, it reveals problematic aspects with the data used in a recent SDA by Feng et al. (2015), which lead to questionable conclusions. Feng et al. (2015) quantified the contributions from the economic recession and changes in the fuel mix and found, consistent with Nelson et al. (2015), that the largest decrease in emissions over the period 2007–2013 was due to decreased consumption during the recession of 2007–2009, with changes in the fuel mix playing a comparatively smaller role. However, by only focusing on changes in the total fuel mix, Feng et al. (2015) could not separately quantify the impact of renewables and natural gas. In a response to Feng et al. (2015), Kotchen and Mansur (2016) also suggested that Feng et al. understated the impact of natural gas and that the shale gas boom alone had reduced total U.S. CO_2 emission by 2.1–4.3% between 2007 and 2013. This range for the contribution from natural gas, however, is wide, and neither of these previous analyses specifically considered the impact of renewables.[1]

By separately quantifying the impacts of renewables, nuclear energy, and natural gas, we find that changes in the composition of U.S. energy supply contributed 6.3% (SDA) to 7.5% (IDA) of the total emissions reduction of 10% between 2007 and 2013, out of which natural gas contributed 2.5% (SDA) to 3.6% (IDA) and renewables 2.3% (SDA) to 3.3% (IDA). These results are within the range for natural gas suggested by previous analyses such as Kotchen and Mansur (2016) but, unlike those prior analyses, also show that renewables have been as important as natural gas in reducing U.S. CO_2 emissions.

2. Using IDA and SDA to analyze the role of renewables in CO2 emission trends

As explained by Wang et al. (2017), results given by decomposition analyses can help researchers and policy makers understand the driving forces behind changes in energy use or emissions. The rationale of decomposition analysis is to decompose the change in a variable of interest, such as total CO_2 emissions, into a sum of changes in each of a number of key driver variables (such as total energy use, the share of renewables, and the composition of fossil fuel energy use). The approach is based on defining an identity where the variable of interest equals the product of all the driver variables. The different methods of decomposition analysis offer different approaches on how to decompose an overall change in this multiplication into a sum of changes in each driver variable. Formally, this is achieved by taking the derivative over time of the variable of interest and applying the product rule, thus resulting in the sum of the derivatives over time of the driver variables. The decomposition methods then offer different approaches on how to go from infinitesimal changes (derivatives) to changes between time periods such as years or longer periods, depending on data availability (cf. Löfgren and Muller, 2010; Muller, 2007). The effects identified in an IDA make it possible to draw conclusions regarding the impacts of improved energy efficiency (activity intensity effect), adjusting economy structure (structure effect) and decarbonizing energy mix (energy mix effect). The energy mix however is commonly introduced as one of the explanatory factors without an explicit consideration or separation of renewables and nuclear energy, as with the analyses done by Feng et al. (2015) and Steenhof and Weber (2011). However, with the rise of renewables and their expected continued cost decreases, it will become increasingly important to analyze the role of renewables in CO_2 emission trends. We here introduce an example for how to do so in both IDA and SDA. In particular, we decompose the changes in the energy mix into three components: changes in the energy supply from renewables, nuclear energy, and changes in the fossil fuel mix. This allows us to quantify what the rise of renewables and the recent sharp decrease in their costs have meant for U.S. CO_2 emissions, and also to separately quantify the contribution from changes in the fossil fuel mix triggered by the shale gas boom and lower natural gas prices.

We present results using both IDA and SDA and note just like Wang et al. (2017) and Hoekstra and van den Bergh (2003) that IDA offers insights on the impacts of energy composition, economic structure and economic output, while SDA sheds light on the effects of production technology and consumption patterns. The main advantage of SDA lies in a detailed coverage of a number of technological and final demand effects related to the sectoral structure and between-sector exchange as captured in input-output tables. These aspects are however not relevant for the identification of the role of renewables in IDA, as they do not specifically affect different energy types (IEA, 2016a). The main reason we also perform an SDA is to be able to compare our results to the SDA performed by Feng et al. (2015) which highlights some methodological pitfalls to consider when assessing the impacts of changes in the energy mix using SDA.

3. Data and methods

We here present the data used and the formulas for separating the renewables, nuclear and fossil fuels effects in IDA and SDA.

3.1. Data

In the IDA, we utilize energy statistics from the U.S. Energy Information Administration's (EIA) Monthly Energy Review for the residential, commercial, industrial, transportation and power sectors on CO_2 emissions (Tables 12.2–12.6, respectively), on primary energy use (Tables 2.2–2.6, respectively), and on net electricity generation from the power sector (Table 7.2b) (EIA, 2015). We use the coal, natural gas, petroleum, and renewable energy (for the transportation sector equivalent to biomass energy) categories as defined by the EIA. Detailed information about data definitions and sources can be found for the primary energy data in EIA (2017a), for the CO_2 emissions data in EIA (2017b), for the power sector net generation data in EIA (2017c), and for renewable energy data in EIA (2017d).

The SDA is instead based on energy accounts created to match with an input-output table for national accounts. The basis for the Input-Output tables are the Make and Use tables by the Bureau of Economic Analysis (BEA) (2016a, 2016b). We adjusted the obtained Input-Output tables from current prices to constant prices (base year 2009) using the Chain-Type Price Indexes for Gross Output by Industry, developed by the Bureau of Economic Analysis (BEA) (2016c). For the compilation of energy use data, we followed the technical report on the compilation of the World Input-Output Database (WIOD) environmental data by Genty et al. (2012), whenever it was applicable. The authors of this report demonstrate how to get from energy balances to energy accounts that correspond to the national accounting framework based on the extended world energy balances provided by the International Energy Agency (IEA) (2016b). Schneider (2016) provides a detailed explanation of this data compilation process for the SDA. The corresponding CO_2 emissions data was taken from IEA (2016a).

Due to the different data used, there are differences in the total U.S. CO_2 emission estimates used for the IDA and the SDA. The reason is that the energy statistics used for the IDA follow the territorial principle, meaning that all energy use and emissions that take place in a certain territory (e.g., a country) are accounted for, irrespective of the legal status of the emitting unit as a resident or not. In contrast, the national accounts used for the SDA follow the residence principle, i.e., all energy use and emissions by a resident of the country are included, whether they are taking place within or outside this territory (Genty et al., 2012). Important differences between the national accounts and the

[1] A previous version of this paper was shared with Feng et al. in September 2015. In their reply to Kotchen and Mansur (2016), Feng et al. (2016) subsequently made brief reference to the role of renewables.

energy statistics stem from road, air and water transport by residents abroad. Notably, the territorial principle in the IDA is consistent with the rationale behind the greenhouse gas (GHG) emission inventories submitted under the United Nation's Framework Convention on Climate Change (UNFCCC), while the residence principle of the SDA is not.

3.2. Index decomposition analysis

The results from the IDA are based on the additive logarithmic mean divisia index (LMDI) method recommended by Ang (2004) and described in detail in Ang (2005). The IDA decomposes CO_2 emissions from the five sectors defined in the EIA energy data, i.e., the residential, commercial, industrial, transportation and power sectors. CO_2 emissions from direct energy use in the residential, commercial, industrial and transportation sectors were decomposed using primary energy demand as an output proxy (cf. Löfgren and Muller, 2010). The power sector CO_2 emissions were instead decomposed using net electricity generation as the output.

The factors contributing to CO_2 emission changes considered for the end-use sectors (residential, commercial, industrial and transportation) are:

- Changes in primary energy demand.
- Changes in the shares of renewable and non-renewable energy in primary energy use.
- Changes in the relative shares of natural gas, coal and petroleum in fossil fuel use (i.e., fossil fuel switching).
- Changes in the emission intensity per unit of primary energy for natural gas, coal and petroleum.

The IDA identity for direct CO_2 emissions in the end-use sectors which makes it possible to decompose the change in CO_2 emissions between two years into the above listed drivers as a primary energy demand effect, a renewable energy effect, a fossil fuel substitution effect and an emission intensity effect, respectively, can be written:

$$CO2_{ij} = p_i{}^*r_i{}^*f_{ij}{}^*e_{ij} \tag{1}$$

where $CO2_{ij}$ is annual CO_2 emissions in million tonnes (Mt) from fossil fuel category j in sector i. For each sector i, p_i stands for the primary energy demand in British thermal units (Btu), r_i for the non-renewables share in total primary energy (i.e., the share of primary energy use *not* provided by renewable energy which is how the impact of renewables is operationalized in the calculations because renewable energy does not give rise to CO_2 emissions and therefore do not form an explicit part of the identity), f_{ij} for the share of fossil fuel category j in total fossil fuel primary energy and e_{ij} for the CO_2 intensity in tonnes of CO_2 per Btu of fossil fuel category j. The fossil fuel categories are coal, natural gas, and petroleum products. Note that mathematically, CO_2 emissions from the different fossil fuel categories are decomposed separately so that the fossil fuel factor in the formulas represents the share of fossil fuel category j in total fossil fuel primary energy use in sector i, and that the total fossil fuel substitution effect, just like the other effects, is calculated as the net sum over the three fossil fuel categories and the five sectors in line with Eq. (3) below.

The factors contributing to CO_2 emission changes considered for the power sector are comparable to the factors for the end-use sectors, but are based on net electricity generation instead of primary energy use, which allows us to add nuclear energy and heat rate as two additional factors:

- Changes in electricity demand (as represented by total net electricity generation).
- Changes in the share of renewable energy in net electricity generation.
- Changes in the share of nuclear energy in net electricity generation.
- Changes in the relative shares of natural gas, coal and petroleum in total fossil fuel net generation (i.e., fossil fuel switching).
- Changes in the average heat rate for natural gas, coal and petroleum based electricity generation, respectively, (i.e., changes in the average efficiency of the power plant fleet).
- Changes in the emission intensity per unit of primary energy for natural gas, coal and petroleum, respectively.

The IDA identity for the power sector which makes it possible to decompose the change in CO_2 emissions between two years into the above listed drivers as an electricity demand effect, a renewable energy effect, a nuclear energy effect, a fossil fuel substitution effect, a heat rate effect and an emission intensity effect can in turn be rewritten

$$CO2_{power,\ j} = s_{power}{}^*r_{power}{}^*n_{power}{}^*f_{power,j}{}^*c_{power,j}{}^*e_{power,j}, \tag{2}$$

where s_{power} stands for total annual net electricity generation in megawatt hours (MWh), r_{power} for the non-renewables (i.e., the share of net electricity generation not provided by renewables, that is fossil fuel plus nuclear energy) share in total net generation, n_{power} for the share of total fossil fuel net generation in total non-renewables net generation, $f_{power,j}$ for the share of fossil fuel category j in total fossil fuel net generation, $c_{power,j}$ for the heat rate of fossil fuel category j in Btu per MWh and $e_{power,j}$ for the CO_2 intensity in tonnes of CO_2 per Btu of fossil fuel category j. Using the same logic as for the end-use sectors, the renewable energy factor is calculated by taking the remainder after the share of renewable energy in total net generation has been subtracted since only sources that give rise to CO_2 emissions are explicitly featured in the identity. Similarly and for the same reason, the impact of nuclear energy is operationalized by taking the remainder after the share of nuclear energy has been subtracted from non-renewable net generation.

The calculations of the effect associated with each factor in the above identities are completely consistent with the general formulae presented for additive LMDI in Ang (2005). Thus the total renewable energy effect is given by:

$$\text{Renewable energy effect} = \sum_i \sum_j \frac{CO2_{ij}^{2013} - CO2_{ij}^{2007}}{\ln CO2_{ij}^{2013} - \ln CO2_{ij}^{2007}} \ln\left(\frac{r_i^{2013}}{r_i^{2007}}\right) \tag{3}$$

To allow us to focus on the disaggregation of the fuel mix effect when we present our IDA results in Fig. 1, we present the total primary energy demand effect as the total sum of the electricity demand and heat rate effects in the power sector, as well as the primary energy demand effects in the four end-use sectors. Similarly, the fossil fuel substitution effect is the sum of this effect across the sectors and includes the CO_2 intensity effects, since this effect is in fact representing intra-fossil fuel substitution (e.g., distillate fuel oil to residual fuel oil within petroleum products), and is negligible compared to the size of the fossil fuel substitution effect from switching between natural gas, coal and petroleum.

3.3. Structural decomposition analysis

The structural decomposition analysis involves nine different multiplicative contributing factors, whose influences on the variations in the CO_2 emissions from year to year are analyzed, while the total of direct household emissions HH_{dir} is simply added to the otherwise purely multiplicative equation (see e.g., Miller and Blair, 2009; Feng et al., 2015). The nine factors considered in the SDA can be divided into energy demand and energy supply side factors, respectively. The SDA thus allows for a decomposition of the energy demand side factor not possible in our IDA while the energy supply side factors in the SDA are consistent with the factors considered in the IDA.

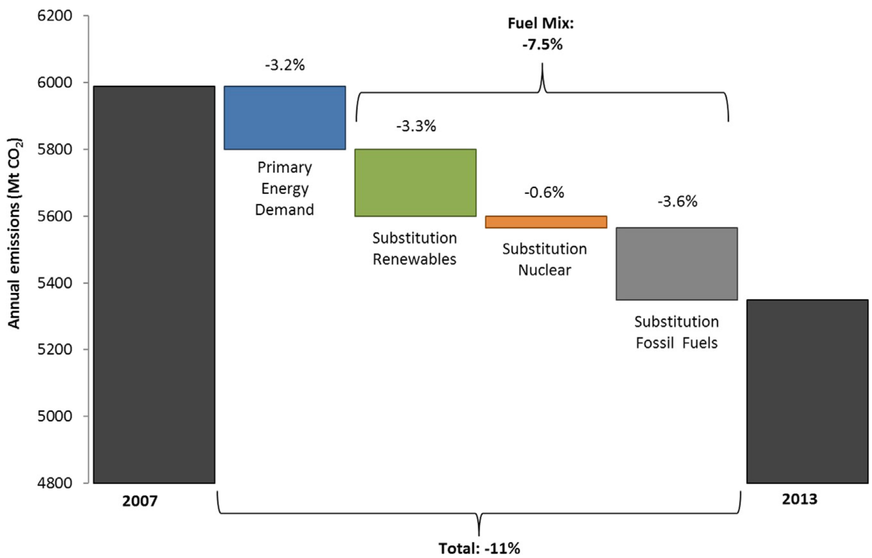

Fig. 1. Index decomposition of the difference in U.S. energy-related CO_2 emissions between 2007 and 2013: energy supply. The black bars show the annual emissions in 2007 and 2013, respectively. The blue bar shows the contribution from primary energy demand to the difference in emissions between 2007 and 2013; the green bar the contribution from renewable energy; the orange bar the contribution from nuclear energy; and the grey bar the contribution from cross-fossil fuels substitution (on net natural gas substituting for coal and petroleum products).

Energy demand side factors

- Changes in population size.
- Changes in consumption volume (in real USD per capita).
- Changes in consumption patterns (relative output shares of different industry sectors).
- Changes in the production structure (the input mix).
- Changes in the energy intensity of production.

Energy supply side factors

- Changes in the share of renewable energy in energy use.
- Changes in the share of nuclear energy in energy use.
- Changes in the relative shares of fossil fuel and waste in energy use (fossil fuel switching).
- Changes in the emission intensity for the fossil fuel and waste categories.

The SDA identity which makes it possible to decompose the change in CO_2 emissions between two years into the above listed drivers is:

$$CO2 = \boldsymbol{EmI}*\boldsymbol{FFWa}*\boldsymbol{Nu}*\boldsymbol{Re}*\boldsymbol{EnI}*\boldsymbol{L}*\boldsymbol{y_s}*y_v*p + HH_{dir},$$

where $CO2$ is a scalar and denotes the total annual CO_2 emissions in Mt. The first four factors represents the energy supply side and the remaining six the energy demand side. The emission intensity $\boldsymbol{EmI}$ is represented by a 1 × 9 row vector, which comprises the CO_2 emissions in Mt per kilotonne of oil equivalent (ktoe) of energy use for the nine different fossil fuel and waste energy sources used in the analysis. Fossil fuels and waste $\boldsymbol{FFWa}$ is depicted by a 9 × 71 matrix, where for each of the 71 columns representing the 71 industries used in the analysis the share of each energy source (rows) in total energy use from fossil fuels and waste is listed. Similar to the logic from the IDA explained above, nuclear $\boldsymbol{Nu}$ is a 71 × 71 diagonal matrix, where the diagonal contains the share of the energy use from fossil fuels and waste in the total non-renewable energy use for each of the 71 industries. The renewables $\boldsymbol{Re}$ are similarly represented by a 71 × 71 diagonal matrix where the diagonal comprises the share of the energy use from fossil fuels and waste as well as nuclear energy in the total energy use (i.e., just like in the IDA the remainder after the share of renewables in total energy use has been subtracted). All three variables $\boldsymbol{FFWa}$, $\boldsymbol{Nu}$ and $\boldsymbol{Re}$ do not only include the energy sources themselves (primary energy products) but also the electricity and heat (secondary energy products) that are produced based on the energy sources within each variable. Since in economic terms, each individual production step is represented with its full value in the input-output tables (production structure $\boldsymbol{L}$, see below) no matter the intermediate products, each energy production step needs to be counted individually as well to match the classification. This means that the MJ in e.g., coal are counted in a first step as primary energy. Then, in a second step, the MJ are counted again in the form of electricity as secondary energy. Even though the energy contained in coal is converted to electricity and therefore essentially the same energy in both steps, it is counted twice to match the inherent double-counting of the input-output tables. This inherent feature of the SDA is one reason, in addition to the choice of allocation method discussed below, why the SDA will yield somewhat different results to an IDA.

The energy intensity $\boldsymbol{EnI}$ is represented by a 71 × 71 diagonal matrix, where the diagonal comprises the energy use in ktoe per total commodity output in USD for each of the 71 industries. The production structure $\boldsymbol{L}$ is depicted by the total requirements matrix, which entails all interindustry transactions and takes the shape of a 71 × 71 matrix. The consumption patterns $\boldsymbol{y_s}$ are represented by a 71 × 1 column vector that comprises the shares of total final demand in the 71 industries, whereby the sum of the column vector equals 1. The consumption volume y_v in real USD per capita and the population p are both scalars denoting the sum of total final demand based on all final demand categories and the US population size, respectively.

Similar to how we chose the additive LMDI for the IDA, the SDA requires a choice of approach for how to allocate the contributions across the factors in the above identity since there is no unique solution for the decomposition. Dietzenbacher and Los (1998) advocate averaging all possible first-order decompositions. This method was used by Feng et al. (2015) and we similarly use it here. For further details, we refer to Schneider (2016).

When we present results from the SDA for the energy supply side factors in Fig. 2, similar to the results from the IDA, we present the total primary energy demand effect as the total sum across all sectors and all energy demand side factors (which are instead disaggregated in Fig. 3) to be able to focus on the fuel mix effects. Fig. 2 presents the sum across all the 71 sectors for the renewables, nuclear and fossil fuel substitution effects. Consistent with Fig. 1, the fossil fuel substitution effect also includes the energy intensity effect, but again, since this intra fuel substitution effect is negligible, the size of this factor is driven by a switch from coal and petroleum towards natural gas.

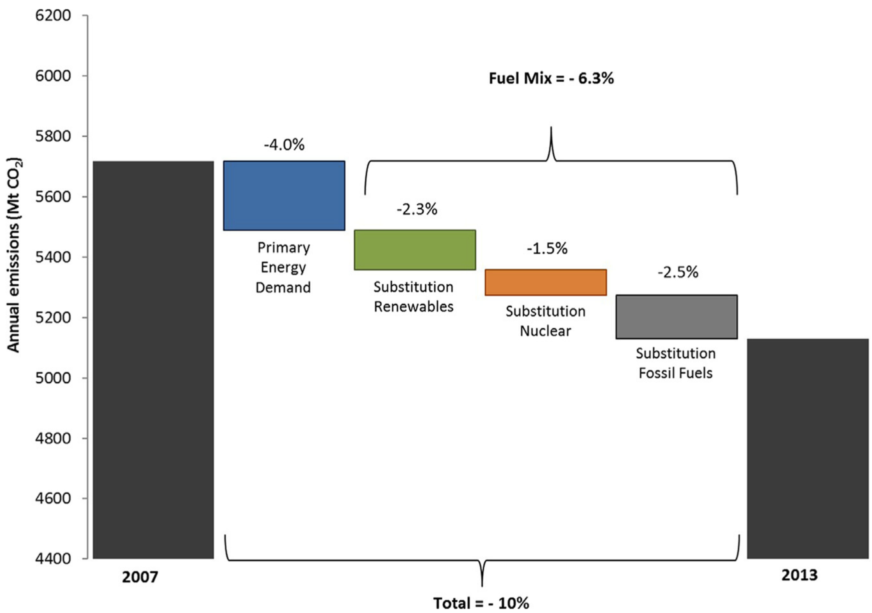

Fig. 2. Structural decomposition of the difference in U.S. energy-related CO_2 emissions between 2007 and 2013: energy supply. The black bars show the annual emissions in 2007 and 2013, respectively. The blue bar shows the contribution from primary energy demand to the difference in emissions between 2007 and 2013; the green bar the contribution from renewable energy; the orange bar the contribution from nuclear energy; and the grey bar the contribution from cross-fossil fuels substitution (on net natural gas substituting for coal and petroleum products).

4. Results and discussion

4.1. The impact of renewables on U.S. CO_2 emissions between 2007 and 2013

We first present results from the IDA. With the IDA, we calculate a disaggregated energy mix effect and separate out the effect of changes in renewable and nuclear energy use from the fossil fuel substitution effect. The remaining CO_2 emission changes net of the energy mix impact are due to changes in primary energy demand. Fig. 1 presents the results. The total CO_2 emission decrease between 2007 and 2013 was 639 Mt, down by 10.7% from 5989 Mt in 2007 (EIA, 2015). According to the IDA, two-thirds of this total decrease in CO_2 emissions were due to changes in the energy mix, with 199 Mt (3.3%) from renewables substituting for fossil fuels and 215 Mt (3.6%) from changes in the fossil fuel mix itself. 35 Mt (0.6%) are attributed to increases in nuclear generation and the remaining 190 Mt (3.2%) to changes in primary energy demand. The fossil fuel mix effect is primarily driven by natural gas substituting for petroleum and coal; the renewables effect is primarily driven by increases in intermittent renewable generation in the power sector, but also by increased use of biofuels in the transportation sector.

Next, we present the SDA results. Fig. 2 illustrates the results from the structural decomposition analysis on the energy mix impacts. With the residence principle used for the SDA as described in the methods section, the total CO_2 emission decrease between 2007 and 2013 was instead 589 Mt, down by 10.3% from 5718 Mt in 2007. According to the SDA, 353 Mt CO_2 or 6.2% came from changes in the composition of energy supply, i.e., 60% of the total change in CO_2 emissions was driven by changes in the U.S. energy mix. Out of this total, 132 Mt CO_2 or 2.3% came from an increase in the energy supply from renewables, while 83 Mt (1.5%) came from an increase in nuclear electricity generation and 138 Mt (2.4%) came from changes in the fossil fuel mix, i.e., from natural gas substituting for coal and petroleum products. The blue bar shows the aggregate impact from the different drivers of primary energy demand, to be discussed in the next section, which was in total a net reduction of 236 Mt CO_2.

Due to the aforementioned differences in the energy statistics data

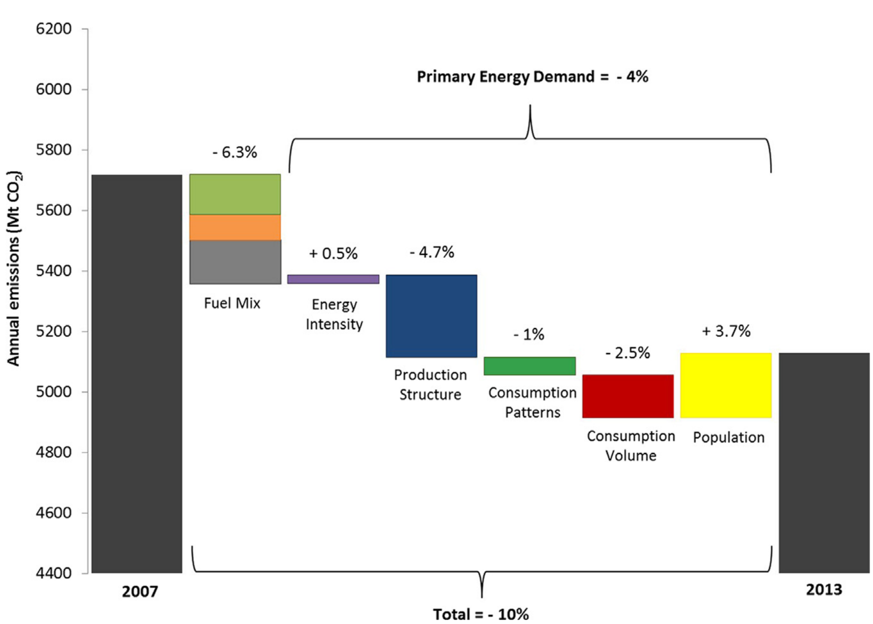

Fig. 3. Structural decomposition of the difference in U.S. energy-related CO_2 emissions between 2007 and 2013: energy demand. The black bars show the annual emissions in 2007 and 2013, respectively. The second bar shows the contribution from changes in the fuel mix consistent with Fig. 2: green is for renewable energy; orange for nuclear energy; and grey for cross-fossil fuels substitution (on net natural gas substituting for coal and petroleum products). The other bars decomposes the change in primary energy demand into five effects: purple is changes in energy intensity of production, dark blue is changes in the composition of the production sector, green is changes in the composition of consumption, red is changes in consumption volumes, and yellow is changes in the size of the U.S. population.

compared to national accounts, the results from the IDA and SDA are not directly comparable. However, both methods speak to the role of renewables in explaining the magnitude of the U.S. CO_2 emissions decrease, no matter whether these emissions are defined according to the territorial principle or the residence principle. Both analyses lead to the conclusion that renewables were as important as natural gas in driving down U.S. CO_2 emissions between 2007 and 2013. We emphasize that the data used in the IDA is more consistent with national GHG emissions reporting and the definition of national emissions used under the Kyoto Protocol and the subsequent Paris agreement. An IDA therefore provides more informative results on the drivers behind changes in official national emission figures than an SDA, while at the same time requiring less data and being more straightforward to perform.

4.2. The impacts of production technology and consumption patterns on U.S. CO_2 emissions between 2007 and 2013

The benefit offered by the much higher data requirements for the SDA is that it makes it possible to further explain the changes in primary energy demand, and how changes on the energy demand side of the U.S. economy contributed to the CO_2 emission decline between 2007 and 2013. The drivers of primary energy demand included in the SDA are: changes in the energy intensity of the production sector, changes in the structure of the U.S. production sector, changes in consumption patterns, changes in consumption volume and lastly changes in the size of the U.S. population.

Fig. 3 disaggregates the drivers of the changes in primary energy demand. According to the SDA results, the most important factor was changes in the mix of production inputs, which contributed to reductions of 271 Mt, or 4.7% compared to CO_2 emissions in 2007. Reductions in the amount of spending, i.e. consumption volume, contributed an additional 141 Mt of CO_2 reductions or 2.5%–primarily driven by the recession in 2008–2009. Changes in the type of goods and services that Americans consumed reduced CO_2 emissions by an additional 59 Mt or 1%. Counteracting these reductions were a slight increase in the energy intensity of production, which increased emissions by 29 Mt or 0.5%. Population growth also increased energy demand and thereby CO_2 emissions by an additional 213 Mt or 3.7%.

Therefore, the most important drivers for CO_2 emission reductions on the energy demand side were a shift towards a less energy-intensive production structure and a reduction in consumption volume primarily related to the recession in 2008–2009.

5. Methodological pitfalls in structural decomposition analysis

Both IDA and SDA are methodologically straightforward, but some challenges can arise related to data availability and data preparation (see Löfgren and Muller, 2010). We use our results to point out a particular challenge that may arise from the different structure of the available data sources when preforming an energy-related SDA. We illustrate this by comparing our results with an earlier SDA study that addresses U.S. CO_2 emissions over the same period done by Feng et al. (2015). Overall, our estimated contributions from the combined fuel mix changes from renewables, natural gas and nuclear are significantly larger than the total fuel mix impacts estimated by Feng et al. (2015) – 6.3% versus their estimate of 4.4%. There are two explanations for this, which highlight the need for very careful consideration and adjustments of the underlying data when performing an SDA. The first is related to how renewables are accounted for. In an SDA, where inputs are based on primary energy input, electricity generation from renewables need to be adjusted from a secondary energy to primary energy basis to put them on par with fossil fuels. For example, 1 MJ of coal used for electricity is not comparable to 1 MJ of electricity generated by a wind turbine because of the conversion losses at the coal plant. One way of addressing this bias is to adjust the renewable electricity numbers by the average conversion efficiency of fossil fuel plants. This method is used by EIA (see EIA, 2017d) and is the approach that we have taken. If this adjustment is not done, the contribution from renewables will be underestimated.

Secondly, Feng et al. (2015) have combined two different sets of data – the World Input-Output Database (WIOD) and the EIA energy and emissions data. One of the two data sets uses the territorial principle (EIA data) whereas the other data set uses the residence principle (WIOD data). Combining the two data sets bears a very high risk of leading to distorted results and conclusions since the underlying datasets are inconsistent. For example, the economic data (WIOD, residence) includes all American plane carriers (national and international), while the emission and energy data (EIA, territorial) only includes national airplane carriers or national air traffic.

This discussion illustrates the crucial importance of careful and consistent data adjustments for the SDA to make sure that the energy and emissions data correctly correspond to the sectoral definitions in the input-output table. These complications do not arise for an IDA where the only requirements for the calculations are energy statistics and CO_2 emissions data that follow the same sectoral divisions.

6. Conclusion and policy implications

The role of the switch from coal to natural gas in reducing U.S. emissions from their 2007 peak has been well documented (see Afsah and Salcito, 2013; Gold, 2013; IEA, 2012; Hanger, 2012; Kotchen and Mansur, 2016; Melillo, 2014). In part, that is due to the novelty of the factor, and the attention around the so called shale gas boom. In part, it is because of available data: the role of fossil fuels in U.S. CO_2 emissions accounting is well understood—not so for renewables. Historically, they have not been analyzed explicitly because they played a small role in the overall energy mix. That is no longer the case. Our decomposition analyses show an example of how to assess the contribution from renewables to CO_2 emissions reductions, using the case of the U.S emission decrease between 2007 and 2013. Our results show that renewables contributed somewhere between a fourth and a third of the roughly 10% reduction in U.S. energy-related CO_2 emissions over this period. This is at the same level as the impact from changes in energy demand and from natural gas.

These results do not diminish the role of the coal-to-natural gas switch. However, it is important to keep in mind the role of methane leakage along the natural gas supply chain, which significantly reduces the net climate benefits of natural gas and the magnitude of which has previously been underestimated (Alvarez et al., 2012; Allen et al., 2013; Mitchell et al., 2015). Similarly, it is also worth noting that the net GHG benefit of biofuels depends on factors such as the type of feedstock, nitrogen fertilizer use as well as potential indirect land use impacts (see e.g., Bureau et al., 2010; Huang et al., 2013; Mosnier et al., 2013; Searchinger et al., 2008).

Structural shifts in the U.S. economy also contributed to the 10% decrease in the country's CO_2 emissions. Specifically, the U.S. production sector shifted towards less energy intensive inputs and the downturn in consumption related to the recession also contributed to reducing energy demand and CO_2 emissions.

As the cost of renewables continues to decrease in the future and we see further renewable capacity expansion in the electricity sector, it will be increasingly relevant for researchers and policy makers to track their role in CO_2 emissions trends. Our analysis provides an example and approach for how to do so using readily available data. All else equal, such tracking may point to the need to further support renewables deployment in service of energy sector emissions reductions, and like this analysis - highlighting the overemphasis on the role of natural gas in past analyses –, serve to nuance policy makers' views of the underlying drivers of CO_2 emissions.

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