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From a rise in B to a fall in C? SVAR analysis of environmental impact of biofuels

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ABSTRACT

This is the first paper that econometrically estimates the impact of rising *B*ioenergy production on global CO_2 emissions. We apply a structural vector autoregression (SVAR) approach to time series from 1961 to 2009 with annual observation for the world biofuel production and global CO_2 emissions. We find that in the medium- to long-run biofuels significantly reduce global CO_2 emissions: the CO_2 emission elasticities with respect to biofuels range between −0.57 and −0.80. In the short-run, however, biofuels may increase CO_2 emissions temporarily. Our findings complement those of life-cycle assessment and simulation models. However, by employing a more holistic approach and obtaining more robust estimates of environmental impact of biofuels, our results are particularly valuable for policy makers.

Contents

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1. Introduction

An often used argument for supporting biofuel is its potential to lower greenhouse gas emissions compared to those of fossil fuels. Carbon dioxide (CO_2) is of particular interest, as it is one of the major greenhouse gases which cause climate change. Although, the burning of biofuel produces CO_2 emissions similar to those from fossil fuels, the plant feedstock used in the production absorbs CO_2 from the atmosphere when it grows.[1] After the biomass is converted into biofuel and burnt as fuel, the energy and CO_2 is released again. Some of that energy can be used to power an engine, whereas other part of CO_2 is released back into the atmosphere.

The extent to which biofuels lower greenhouse gas emissions compared to those of fossil fuels depends on many factors, some of which are more obvious (direct effects), whereas others are less visible (indirect effects). An example of the former is the production method and the type of feedstock used. An example of the latter is the indirect land use change, which has the potential to cause even more emissions than what would be caused by using fossil fuels instead [14]. Therefore, when calculating the total amount of greenhouse gas emissions, it is highly important to consider both the direct and the indirect effects which biofuels may cause on the environment [34,9,16,17,11,5,29,38,33,6].

Considering all these aspects makes the calculation of environmental impacts of biofuels a complex and inexact process, which is highly dependent on the underlying assumptions. Therefore, when comparing the amount of greenhouse gas emissions across different types of fuels, usually, the carbon intensity of biofuels is calculated in a "Life-cycle assessment" (LCA) framework, the main focus of which is on the direct effects: emissions from growing the feedstock (e.g. petrochemicals used in fertilisers); emissions from transporting the feedstock to the factory; emissions from processing the feedstock into biofuel; emissions from transporting the biofuel from the factory to its point of use; the efficiency of the biofuel compared with standard diesel; the benefits due to the production of useful by-products (e.g. cattle feed or glycerine), etc.[2]

One of such LCA calculations, which was done by the UK government, is presented in Fig. 1. The estimates reported in Fig. 1 suggest that depending on the type of fuel and the place of biofuel production, biofuels can emit 34–86% CO_2 compared to fossil fuels (100%) per energy unit. The figure also suggests that there is a large variation in the CO_2 savings between different types of biofuels, ranging from 38% for palm oil to 73% for soy grown in Brazil.

While serving as a practical tool for assessing the environmental impacts of biofuels (and comparing with those of fossil fuels), most of the LCA calculations do not consider the induced indirect effects, such as the indirect land use change, carbon leakage, changes in crop yield, substitution between fuels, and consumption effects, and hence may be biased [10,23]. Depending on the relative strength of the different indirect channels, the bias can be either upward or downward. Moreover, the LCA studies provide little insights about the inter-temporal dynamics of environmental impacts of biofuels, which however are important for policy makers.

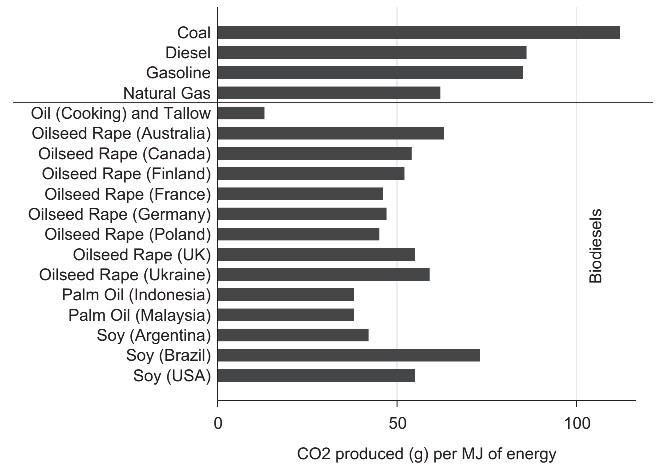

Fig. 1. Carbon intensity of biofuels and fossil fuels. Source: own calculations based on the UK Government data. Notes: *X* axis measures the CO_2 in gram emitted per Megajoule of energy produced.

In order to account for the induced indirect effects of biofuels, simulation models (partial equilibrium (PE) and computable general equilibrium (CGE)) have been developed and applied. Usually, PE and CGE models take the technical coefficients of biofuel production and CO_2 emission as given, and simulate CO_2 emissions under alternative policy regimes or model assumptions. An important advantage of simulation models is that they allow for substitution possibilities both on the energy production side and energy consumption side and, in addition, CGE models account for economy-wide induced general equilibrium effects.

While being able to account for important indirect environmental effects, both PE and CGE models suffer from their sensitivity to calibrated parameters. This in turn significantly widens the confidence interval of simulation results, and increases uncertainty about the true impact of biofuels on environment.[3]

The objective of the present study is to fill this research gap and to estimate the environmental impacts of biofuels, by explicitly addressing the above mentioned weaknesses of both LCA and CGE studies. First, by employing a structural vector autoregression (SVAR) approach, where all variables can be modelled as endogenous, we are able to account for all direct and induced indirect effects. Second, by estimating the underlying structural parameters on reasonably long time-series data econometrically, we are able to ensure statistically significant and robust results.

We find that in the medium- to long-run biofuels significantly reduce global CO_2 emissions. The estimated global CO_2 emission elasticities range between -0.57 and -0.80. In the short-run, however, biofuels may increase CO_2 emissions temporarily (elasticity 0.57). Our findings complement those of life-cycle assessment and simulation models. However, by employing a more holistic approach and obtaining more robust estimates of environmental impact of biofuels, our results are particularly valuable for

[1] Plants absorb CO_2 through a process known as photosynthesis, which allows it to store energy from sunlight in the form of sugars and starches.

[2] For a detailed review of LCA studies, see Janda et al. [20,21].

[3] There exist few studies in the literature, where a particular emphasis is devoted to parameterisation and empirical implementation of applied general equilibrium models.

policy makers as they help to better understand the role of biofuels in determining their impact on CO_2 emissions.

The rest of the paper is structured as follows. In Section 2 we summarise the key findings of the previous literature. Whereas the theoretical findings allow us to identify the indirect channels through which biofuels can affect CO_2 emissions, the empirical literature provides a useful benchmark against which to measure our results. The following two sections detail the data sources, explain the construction of our variables, and outline the underlying econometric approach. In Section 5 we apply the SVAR approach to time series from 1961 to 2009 with annual observation at the global level, which include all key variables identified theoretically, and discuss the estimation results. Performing impulse–response analysis we estimate the long-run environmental impact of biofuels. The final section concludes and derives policy implications.

2. Previous literature

2.1. Theoretical hypothesis

Theoretical literature has identified several channels through which a rise in bioenergy can increase CO_2 emissions (indirect land use change, carbon leakage and crop yield effect), as well as several channels through which a rise in bioenergy can reduce CO_2 emissions (fuel substitution effect and consumption effect). Depending on the relative strength of these channels of adjustment, an increase in bioenergy production/consumption can affect CO_2 emissions either positively or negatively.

2.1.1. Channels through which biofuels increase CO_2 emissions

Indirect land use change: Generally, as long as the feedstock is grown on existing cropland, land use change has little or no effect on greenhouse gas emissions. However, there is evidence that increased feedstock production directly affects the rate of deforestation and idle land conversion into agricultural production, causing carbon stored in the forest, soil and peat layers to be released [34,16,17,5,29,33]. The amount of greenhouse gas emissions from deforestation can be so large that the benefits from lower emissions (caused by biofuel use alone) can be negligible for hundreds of years. Biofuel produced from feedstock may therefore cause much higher carbon dioxide emissions than some types of fossil fuels.

The indirect land use change has a positive impact on the total land demand, and hence on CO_2 emissions [7]. Higher biofuel production increases demand for biomass, leading to an upward adjustment of agricultural output (biomass) prices, thus improving land profitability. Increasing agricultural land demand stimulates conversion of idle and forest land into agricultural land, resulting in higher CO_2 emissions.

Carbon leakage: de Gorter and Just [9] were among the first to note that an increase in biofuel production causes a reduction in the world gasoline market price, resulting in higher consumption of fossil fuels and CO_2 emissions. In the literature this effect is known as carbon leakage, where leakage means that emission saving in one place causes emissions to raise in another place.

Bento [3] estimated GHG emissions under different biofuel policies and found that the two main biofuel policies (tax credit and mandate) differ significantly in their impact on GHG emissions. While the tax credit can lead to an increase in the distance travelled and a delay in the adoption of more fuel-efficient cars and hence increase GHG emissions, binding mandates exercise an upward pressure on fuel prices and reduce the distance travelled and hence GHG emissions.

Similar results were achieved by Drabik [12], who analysed the impact of a blender's tax credit, a consumption mandate, and a combination of the two on GHG emissions. Drabik has found that the introduction of ethanol decreases domestic fossil fuel consumption under each biofuel policy regime. However, due to differences in biofuel policies across countries, the global effect of biofuel production is ambiguous. The global CO_2 emissions (when land use change is not considered) decrease only, when ethanol is produced due to a mandate and increase relative to gasoline and petroleum by-products under the tax credit or a combination of mandate and tax credit.

Also Chen et al. [5] have examined the implications of different biofuel policies on GHG emissions. In particular, they analyse the impact of the mandate alone, the mandate accompanied by the tax credit and the mandate accompanied by a CO_2 tax policy. They found that biofuel policies differ in their impact on GHG emissions reduction but all three policy scenarios lead to a reduction in GHG emissions relative to the baseline without any biofuel or CO_2 policy. The emission reductions are partially offset by international carbon leakage effects but the change in emissions remains negative in the benchmark case.

Crop yield effect: Increasing biofuel demand resulting in higher crop prices may stimulate farmers to use more inputs, switch to double-cropping and boost yields. Boosting yields may generate more greenhouse gases when using more fertilisers to produce the marginal yield increase of crops than the average yield [35].

Melillo et al. [28] have combined an economic model of the world economy with a terrestrial biogeochemistry model to explore the environmental consequences of a global cellulosic biofuels program in a long-run. Their model predicts that the indirect land use change causes higher CO_2 loss than the direct land use change, but increases in fertiliser use lead to increase in nitrous oxide emissions which are even more important than CO_2 losses in terms of warming potential.

2.1.2. Channels through which biofuels decrease CO_2 emissions[4]

Fuel substitution effect: It captures the replacement of fossil fuel with biofuels in fuel (or energy) consumption. According to de Gorter and Just [9], if oil supply is considered as “finite” while coal supply is considered as “ unlimited”, then ethanol does not replace any gasoline in this scenario but replaces coal instead. Given that, on average, coal emits 40 percent more CO_2 per BTU than oil, U.S. ethanol, displacing coal rather than oil can additionally reduce CO_2 emissions. Even if more greenhouse gas emission reductions can be achieved, if one takes into consideration that U.S. coal is exported around the world and if those exports would increase due to ethanol production, it might also replace the dirtier (high sulfur) coal in China and in other places around the world.

Similar results have been achieved by Hochman et al. [18], who examine the effect of the structure of the oil market on the GHG emissions reduction due to a biofuel mandate in the U.S. They show that GHG emission reduction is higher if OPEC behaves as a monopolist and reduces oil production in response to the rise of biofuels.

Consumption effect: Greenhouse gas emissions may be reduced if price increase caused by biofuels leads to a decrease in the agricultural commodity demand for food and feed. CO_2 absorbed by crops dedicated to food and feed production is not isolated because people and livestock eat and release CO_2. Thus, if people

[4] First generation biofuels may have a negative impact on CO_2 emissions, depending on how the fuel is produced or grown, processed, and then used [15]. Corn-based ethanol, if distilled in a coal-fired facility, can increase GHG emissions more than gasoline. Cellulosic ethanol on the other hand, produced using the unfermentable lignin fraction for process heat, solar or wind-powered distillery, can be superior to gasoline (unless the biomass feedstock ultimately displace wetlands or tropical forests) [37].

and livestock consume fewer crops, for example because of higher prices, greenhouse gas emissions may decline because of reduced respiration of CO_2 into the atmosphere, lower methane emissions and reduced excretion of carbon through wastes [35]. Cornelissen and Dehue [8] find that around one-third of cereals diverted to ethanol would not be replaced, because of reduced feed and food consumption.

Additionally, distillers grains, a cereal by-product of the biofuel distillation process, are reused for livestock feeding and thus partially neutralise the emission effect of cereal used for biofuels. According to Searchinger [35], 30–40% of the CO_2 absorbed by crops used to ethanol production can also be fed to livestock in the form of distillers grains. This CO_2 is also emitted by livestock, but as livestock would emit this CO_2 even if fed the original grain, there is no direct change in CO_2 emitted, but effectively distillers grains reduce the amount of crops diverted to ethanol and therefore reduce the indirect effects of biofuels [35].

2.2. *Empirical evidence*

Two types of approaches are used in the empirical literature to assess the impact of additional biofuel production on CO_2 emissions: Life Cycle Assessment (LCA) analysis and Computable General (and Partial) Equilibrium (CGE) models. Most of the LCA studies find that biofuels can significantly reduce GHG emissions. Simulation models, on the other hand, provide mixed results, depending on model assumptions and policy scenario considered. However, in general, they tend to find an increase in GHG emissions due to biofuels for several years, before significant GHG savings can be reached.

2.2.1. *Life cycle assessment (LCA) models*

LCA reflects a “well to wheel” estimation of GHG emissions from gasoline production and a “field to fuel tank” measure of emissions from ethanol production [15]. LCA includes all physical and economic processes involved in the life of the product. In the case of fuels, LCA looks at the whole system of the fuel production and consumption beginning with farming, followed by harvesting, processing, distribution, end use and waste disposal [21]. However, in practice, most of the LCA studies include direct effects of the production and combustion of the fuel, but typically ignore the indirect effects (land use change), or treat them poorly [10].

The Greenhouse Gas, Regulated Emissions and Energy use in Transportation (GREET) model, which was developed by the Argonne National Laboratory, includes (direct) soil CO_2 changes associated with the production of biofuel feedstocks, but does not include emissions from the indirect land use change. In the GREET model Wang [39] has evaluated different short-and long-term technologies, and found that the short-term technologies offer smaller emission reductions than the long-term technologies, however the long-term ones are connected with many uncertainties.

Farrell et al. [15] have developed the ERG Biofuel Analysis Meta-Model (EBAMM) to make comparison of data sources, methods and assumptions across different LCA studies. Basing the greenhouse gas accounting on the GREET model, they found that corn ethanol reduces petroleum use by about 95% on an energetic basis and reduces GHG emissions by about 13%.

Plevin and Mueller [32] have developed the Biofuels Emissions And Cost CONnection (BEACCON) model to analyse the effects on ethanol production cost of a price on CO_2 across wide range of dry-grind system configurations and policy options. Their findings are similar to those of Wang [39], suggesting that the short-term technologies offer smaller emission reductions than the long-term technologies.

The Biofuel Energy Systems Simulator (BESS) model was developed by Liska et al. [26] to analyse the life cycles of corn-ethanol systems accounting for the majority of U.S. capacity to estimate greenhouse gas. Direct GHG emissions in the BESS model were estimated to be equivalent to a 48–59% reduction compared to gasoline. The BESS estimates of GHG reductions are twofold to threefold larger than those from earlier models.[5]

The Lifecycle Emissions Model (LEM) is one of the few models that contains a detailed treatment of the indirect land use changes [10]. LEM estimated that corn ethanol does not have significantly lower GHG emissions than gasoline (corn ethanol GHG emissions are estimated between −30% and +20%), and that cellulosic ethanol has only about 50% lower emissions (−80% and –40%). As noted by Delucchi [10], the results were mainly influenced by high estimates of emissions from feedstock and fertiliser production, from land use and cultivation, and from non-CO_2 emissions from vehicles.

Generally, however, it is not straightforward to estimate the indirect effects in LCA models. Even if some methods were proposed, they have not yet been widely adopted in practical applications [23].

2.2.2. *Simulation (CGE and PE) models*

There is a wide range of CGE and PE models that analyse the impact of biofuels on CO_2 emissions. However, due to considerable difference among the model structures, data used, regional coverage, and scenarios simulated, a comparison of simulation results from different studies is not straightforward.

Kancs [24] and Kancs and Wohlgemuth [25] employed the GEM-E3 computable general equilibrium model to simulate the impact of an increase in biofuel production in the EU on CO_2 emissions. Depending on policy instruments, generally, their results suggest that in the short-run GHG emissions may increase due to biofuels, whereas in the medium- and long-run significant GHG savings can be reached.

Searchinger et al. [34] employed a partial-equilibrium simulation model developed by the Food and Agricultural Policy Research Institute (FAPRI) and the Center for Agriculture and Rural Development (CARD) to estimate market responses to increased ethanol production in the U.S. by 56 billion litters above the projected levels for 2016. Their results show that if accounting for land-use changes, emissions from corn ethanol nearly double those from gasoline for each km driven over a 30-year period. Further, their results indicate that GHG savings from corn ethanol would equalise carbon emissions from land-use change in 167 years, meaning emissions increase until the end of that period. In a follow up study, Dumortier et al. [13] used the FAPRI model to estimate the indirect land use change emissions effect of higher U.S. ethanol production. They find that the amortisation period of the carbon emissions from land use changes by corn ethanol's savings is sensitive to assumptions concerning land conversion and yield growth and can range from 31 to 180 years.

Hertel et al. [17] applied the GTAP computable general equilibrium model to simulate the direct and indirect land use changes of the mandate for corn ethanol in the U.S. Their estimates suggest lower increase in emissions induced by land use changes: one-fourth of the value estimated by Searchinger et al. [34]. Their results further suggest that the amortisation period of land use emissions could take around 28 years.

The Forest and Agricultural Sector Optimisation Model (FASOM) used by Beach and McCarl [2] is a dynamic multi-market model of the U.S. forest and agricultural sectors that includes both first- and second-generation biofuels and examines the implications of the renewable fuel standard over the 2007–2022 period. They point to an increase in CO_2 through increased use of fertilisers. By 2022, nitrogen inputs are expected to rise 6.8% and 5.8% for corn and soybean production,

[5] Plevin [31] attempts to explain the differences between the BESS and GREET models in the GREET-BESS Analysis Meta-Model (GBAMM).

respectively, and phosphorus inputs are predicted to rise 12.6% for corn.

Using a stylised model, Hochman et al. [18] examined the effect of the structure of the oil market on the GHG emissions reduction due to a biofuel mandate in the U.S. Their outcome suggests that although the introduction of biofuels changes the composition of the consumed fuel (reduces the quantity of fossil fuel consumed by oil-importing countries by between 0.3% and 0.7%, resulting in less CO_2 emissions per gallon of fuel consumed), it also increases the global fuel consumption by 1.5–1.6% (resulting in more CO_2 emissions). They also show that GHG emissions reduction is higher if OPEC behaves as a monopolist and reduces oil production in response to the emergence of biofuels.

Drabik and de Gorter [11] have estimated the effects of a blend mandate with and without a tax credit on domestic and global GHG emissions. They find that a 10% blend mandate reduces domestic GHG emissions by 4–5% (because it raises the domestic fuel price by 9–13%); world emissions however fall by less than 1%, due to the rebound effect. Blend mandate with a tax credit results in higher emissions than the mandate alone, because it induces more gasoline consumption to maintain a fixed share of biofuels.

Chen et al. [5] have used the Biofuel and Environmental Policy Analysis Model (BEPAM) to determine the effects of biofuel policies on land use and GHG emissions. They found that all three policy scenarios considered (mandate, mandate with tax credit, and mandate with CO_2 tax) lead to a reduction in GHG emissions relative to the state without any biofuel or CO_2 policy. GHG emissions in the U.S. decrease by 2% under the mandate, 3.8% under the mandate with tax credit and 4.6% under the mandate with CO_2 tax. The reduction in GHG emissions achieved after including the international indirect land use change effect is 0.5–1% lower than that above, depending on the size of the indirect land use change effect assumed.

Drabik [12] analysed how biofuel policies affect domestic and international carbon leakage. He found that the world gasoline price declines under all analysed biofuel policies. According to his results, when emissions from land use change are taken into account, corn ethanol emits −16.0, −13.5 or −14.9 percent (under the tax credit, mandate or mandate and tax credit respectively) more CO_2 than gasoline and corresponding petroleum by-products. When emissions from land use change are excluded, corn ethanol increases CO_2 emissions relative to gasoline and petroleum by-products by 2.3 or 1.2 percent (under the tax credit or mandate and tax credit). Global CO_2 emissions decrease by 0.2 percent only, when ethanol is produced due to a mandate.

Chakravorty and Hubert [4] have used a regionally aggregated global model and find that a blend mandate would reduce fuel consumption and direct emissions in the U.S. by 1% in 2022, but increase world emissions by about 50%.

3. Empirical approach

3.1. Estimation issues

The theoretically identified linkages and the previous empirical evidence suggest that energy, bioenergy and environmental systems are mutually interdependent. Theoretical literature has identified three channels through which a rise in bioenergy can increase CO_2 emissions (indirect land use change, carbon leakage and crop yield effect), and two channels through which a rise in bioenergy can reduce CO_2 emissions (fuel substitution effect and consumption effect). The volatile bioenergy sector, fluctuations in the world oil price, etc., suggest that this relationship may be non-linear, because the relative strength of the channels of adjustment depends, among others, on the size of bioenergy sector and fuel price.

The estimation of non-linear interdependencies among interdependent time series in presence of mutually related (cointegrated) variables is subject to several estimation issues. First, in standard regression models, by placing particular variables on the right hand side of the estimable model, the endogeneity of explanatory variables sharply violates the exogeneity assumption in the presence of interdependent time series [27]. Second, non-linearities in the relationship between energy, bioenergy and environmental systems suggest that the standard linear regression model would not be able to capture these non-linearities.

According to the findings from the previous studies discussed in Section 2.2, besides the bioenergy-CO_2 linkages identified in Section 2.1, confounding factors may affect both biofuels production and CO_2 emissions and bias the estimates. For example, energy and bioenergy markets depend on macro-economic developments, such as GDP growth, and population growth. A favourable macro-economic development may induce upward adjustments in both energy and agricultural markets through stimulating production and hence causing land use changes and fuel price rise. These structural adjustments may confound the estimations, causing for example an upward bias in the estimated land use change impact.

3.2. Available data and variable construction

Data availability will largely determine our econometric strategy to address the identified estimation issues. The data used in the empirical analysis are collected from seven main sources: the U.S. Energy Information Administration (EIA), the Institute for Sugar and Alcohol (IAA), the Earth Policy Institute (EPI), Global Trade Analysis Project (GTAP), the Food and Agriculture Organization of the United Nations (FAO), the World Bank and the Carbon Dioxide Information Analysis Center (CDIAC). Table 1 summarises the key data sources and states which variable is derived from each source.

The two key variables necessary for our estimated model are CO_2 emissions and biofuels. The CDIAC calculates CO_2 emissions produced from different types of sources, which are measured in million metric tons of carbon dioxide. Information about world biofuel production is provided by the Institute of Sugar and Alcohol from 1961 to 1974 and by the EPI for the other years. We use biofuel production instead of biofuel prices due to the fact that consistent price data for the study period are not available. Table 1 summarises the key data sources and states which variable is derived from each source.

Our data contain annual observation at global level from 1961 to 2009 for eight variables: World Population, Real World GDP Growth, World Crude Oil Production, World Crude Oil Price, World Biofuel Production, World Total Agricultural Area, Global Wheat Yield, and Global CO_2 Emission. The summary statistics of all variables used in estimations is provided in Table 2.

All variables, except the GDP growth and oil price, are transformed in natural logarithms. Further, each estimated model includes also a constant term and a trend variable in order to account for adjustment over the time, such as technological change.

3.3. Econometric specification

In the context of multiple cointegrated times series, the problem of endogeneity can be circumvented by specifying a Vector Auto-Regressive (VAR) model on a system of variables, because no such conditional factorisation is made a priori in VAR

Table 1
Data sources and variable description.

Variable	JMulTi Code	Unit	Source
World Population	$pop-world$	Thousand head	FAO
Real World GDP Growth	$gdp-g-world$	Percent	World Bank
World Crude Oil Production	$oil-prod-world$	Million barrels per day	EIA
World Crude Oil Price	$oil-price$	USD per 1 barrel	World Bank
World Biofuel Production	$biofuel-prod-world$	Million gallons	IAA, EPI[a]
World Total Agricultural Area	$uaa-world$	Thousand hectares	FAO
Global Wheat Yield	$wheatyield-world$	Hectograms per 1 hectare	FAO
Global CO_2 Emission	$global-CO_2$	Million tons of carbon dioxide	CDIAC
Global CO_2 Emissions from Fossil–Fuels Burning	$fossil-fuel-CO_2$	Million tons of carbon dioxide	CDIAC
Global CO_2 Emissions from Cement Production	$cement-CO_2$	Million tons of carbon dioxide	CDIAC
Land Use Change CO_2 Emissions	$land-use-change-CO_2$	Million tons of carbon dioxide	CDIAC

Notes: EIA, U.S. Energy Information Administration; IAA, Institute for Sugar and Alcohol; EPI, Earth Policy Institute; CDIAC, Carbon Dioxide Information Analysis Center.
[a] IAA 1961–1974, EPI 1975–2010.

Table 2
Summary statistics of data.

Variable	Average	STD	Max	Min
World Population	4,897,104.55	1,132,015.82	6,817,737	3,085,784
Real World GDP Growth	3.56	1.76	6.8	−2.3
World Crude Oil Production	55.73	13.63	73.71	22.45
World Crude Oil Price	21.18	20.07	96.99	1.21
World Biofuel Production	3960.11	5069.29	23,628.59	92.46
World Total Agricultural Area	4,743,816.38	164,874.36	4,943,431.5	4,458,081.8
Global Wheat Yield	21,239.11	5800.58	30,666.6	10,888.66
Global CO_2 Emission	25,401.83	5533.25	35,243.54	15,034.7
Global CO_2 Emissions from Fossil–Fuels Burning	19,784.06	5634.38	30,733.13	9295.85
Global CO_2 Emissions from Cement Production	589.64	344.65	1514.47	165.02
Land Use Change CO_2 Emissions	5028.28	941.33	8067.4	2566.9

Notes: STD, standard deviation.

models. Instead, all variables can be tested for exogeneity subsequently and can be restricted to be exogenous based on the test results. Given these advantages, we follow the general approach in the literature to analyse the causality between endogenous variables and specify a VAR model [27].

Based on the theoretically identified channels through which biofuels may affect CO_2 emissions, we specify an econometrically estimable SVAR model of biofuel production and CO_2 emissions. In order to control for confounding factors, which may affect both biofuels production and CO_2 emissions, we augment the econometric model by including several macroeconomic variables, which have been identified as important in the previous studies.

Our estimable model contains eight endogenous variables: world population in year t, (pop_world_t), real world GDP growth ($gdp\_g\_world_t$), world-wide crude oil production ($oil\_prod\_world_t$), world oil price (oil_price_t), world-wide biofuel production ($biofuel\_prod\_world_t$), total agricultural area (uaa_world_t), global wheat yield ($wheatyield\_world_t$), and global CO_2 emissions ($global\_CO_{2t}$):

$$y_t = \begin{bmatrix} pop\_world_t \\ gdp\_g\_world_t \\ oil\_prod\_world_t \\ oil\_price_t \\ biofuel\_prod\_world_t \\ uaa\_world_t \\ wheatyield\_world_t \\ global\_CO_{2t} \end{bmatrix}$$

In order to identify the structural (SVAR) model and the associated impulse–response functions, we need to specify the covariance matrix and decide on the contemporaneous effects between the endogenous variables. According to Hurwicz [19], a SVAR model of lag order p can be specified as follows:

$$A\left(I_k - A_1 L - A_2 L^2 - \cdots - A_p L^p\right) y_t = A\varepsilon_t = Be_t$$

where A, B and $A_1 \ldots A_p$ are $K \times K$ matrices of coefficients, while e_t is a $K \times 1$ vector of orthogonalised disturbances: $e_t \sim N(0, I_k)$ and $E[e_t e_t'] = 0_k$ for all $s \neq t$. This transformation of the innovation vector ε_t allows us to describe the reaction of each variable in terms of change to an element of e_t. In this way we are able to identify the impulse–response functions.

Assuming that matrices A and B are non-singular, we place parameter restrictions in order to identify the underlying structural model. As usual, we employ the Cholesky decomposition, which only requires the specification of the order of variables. The relationship between residuals in the reduced-form and structural shocks are as follows:

$$\begin{bmatrix} e_t^{pop\_world} \\ e_t^{gdp\_g\_world} \\ e_t^{oil\_prod\_world} \\ e_t^{oil\_price} \\ e_t^{biofuel\_prod\_world} \\ e_t^{uaa\_world} \\ e_t^{wheatyield\_world} \\ e_t^{global\_CO_2} \end{bmatrix}$$

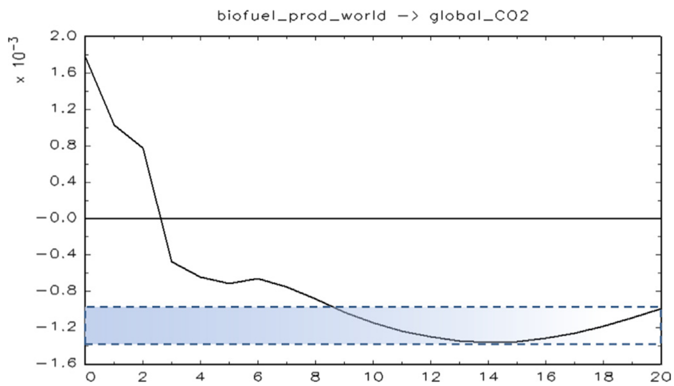

Fig. 2. Impact of an increase in world-wide biofuel production (impulse) of one standard deviation on the aggregated global CO_2 emissions (response). Notes: *Y*-axis measure million metric tons of CO_2 in natural logarithm, *X*-axis captures years.

$$= \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 & 0 & 0 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & 1 & 0 & 0 & 0 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & 1 & 0 & 0 & 0 \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & 1 & 0 & 0 \\ a_{71} & a_{72} & a_{73} & a_{74} & a_{75} & a_{76} & 1 & 0 \\ a_{81} & a_{82} & a_{83} & a_{84} & a_{85} & a_{86} & a_{87} & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_t^{pop\_world} \\ \varepsilon_t^{gdp\_g\_world} \\ \varepsilon_t^{oil\_prod\_world} \\ \varepsilon_t^{oil\_price} \\ \varepsilon_t^{biofuel\_prod\_world} \\ \varepsilon_t^{uaa\_world} \\ \varepsilon_t^{wheatyield\_world} \\ \varepsilon_t^{global\_CO_2} \end{bmatrix}$$

These assumptions impose a recursively dynamic structure to the contemporaneous correlations in the estimated system. The first variable responds only to its own innovation, the second variable reacts to first variable shock plus its own innovation and so on for all the variables. For example, we assume that biofuel production affects emissions contemporaneously, while the inverse effect is only lagged. The last variable in the system (global CO_2 emissions) responds to all shocks, but innovations to this variable have no contemporaneous effect on other variables. Generally, each variable responds to the previous variable innovations and to its own shock. In other words, *B* is a diagonal matrix and *A* is a lower triangular matrix.

4. Results[6]

4.1. Specification tests

In a first step, the stationarity of time series is determined. Unit root tests are accompanied by stationarity tests to establish whether the time series are stationary. The results of the Augmented Dickey Fuller unit root test (ADF), the Phillips Perron unit root test (PP) and the Dickey Fuller Generalised Least Square test (DFGLS) are compared to the results of Kwiatkowski–Phillips–Schmidt–Shin stationarity test (KPSS test) to ensure robustness of the test results. The number of lags of the dependent variable is determined by the Akaike Information Criterion (AIC).

In a second step, the Johansen and Juselius's [22] cointegration method is specified to test for cointegration. As usual, the number of cointegrating vectors is determined by the lambda max test and the trace test. We follow the Pantula principle to determine whether a time trend and a constant term should be included in the estimation model.

As usual in VAR models, we also perform the Akaike Information Criterion, Schwarz Criterion and Hannan–Quinn Criterion specification tests to determine the optimal lag length. According to all three test results, the optimal lag order is one. Hence, we estimate the specified VAR model in levels.

4.2. Aggregated results

The estimation results for the aggregated global CO_2 emissions (impulse–response function) are reported in Fig. 2. In the long-run (10–20 years) an increase in the world-wide biofuel production (impulse) by one standard deviation (1.75038 million gallon) would reduce the global CO_2 emissions (response) by 2.59–3.86 million metric tons (MMt). In Fig. 2 this corresponds to the light-shaded vertical interval between the dashed lines, to which we apply the exponential transformation, as in the estimations it was expressed in natural logarithms. Hence, our results support the previous evidence from the LCA and simulation studies, according to which biofuels contribute to a reduction of CO_2 emissions [39,15,26].

Fig. 2 also suggests that during the first years after the increase in biofuel production the impact on CO_2 emissions would be positive, i.e. CO_2 emissions would increase. It would take around 2–3 years until the positive effect of biofuels would materialise in CO_2 reductions. The initial increase in CO_2 emissions can be explained by the fact that, while biofuel production itself emits CO_2 gasses (which takes place immediately), the substitution of biofuel for fossil fuel in production and consumption is not perfect and takes place sluggishly. These results are in line with findings of simulation models, many of which report an increase in GHG emissions in the first years, before significant GHG savings will be reached [34,28,13,17,1].

Starting from the fourth year, the impact of biofuels on CO_2 is negative, implying that biofuels reduce CO_2 emissions. According to Section 2, the substitution effect and the consumption effect would become stronger than the carbon leakage effect, the crop yield effect and the indirect land use change impact in the medium- to long-run. The estimated annual effect of biofuel increase on global CO_2 emissions increases for around 10 years. It stabilises around 14–15 years after the biofuel shock, followed by a slight decrease in the impact. However, the implications of the long-run results (>15 years) should not be over-emphasised, as our time series (on which the parameter estimates are based) cover only 49 years. Therefore, as a 'confidence interval' we would like to stress to the interval -0.95 to -1.35 (dashed area in Fig. 2).

4.3. Decomposing by source of emission

The aggregated CO_2 emissions reported in Fig. 2 mask a great deal of variation in the CO_2 response to biofuel expansion. In order to separately identify different emission sources, in the following estimations we replace variable 'global CO_2 emissions' with the three major types of CO_2 emissions: fossil fuel emissions, cement emissions, and land use change emissions. The disaggregated estimation results (impulse–response functions) are reported in Fig. 3.

According to the results reported in Fig. 3, in the medium- to long-run, biofuel expansion would reduce CO_2 emissions from fossil fuels and from cement production. The reduction of fossil fuel CO_2 emissions can be largely attributed to the substitution effect and the consumption effect, whereas the reduction of cement CO_2 emissions can likely be attributed to the substitution effect (see Section 2.2). In contrast, biofuel expansion would increase CO_2 emissions related to the indirect land use change in the medium- to long-run (bottom panel in Fig. 3). These results are in line with the theoretical hypothesis discussed in Section 2.1.

[6] The estimations were performed using JMulTi 4.24.

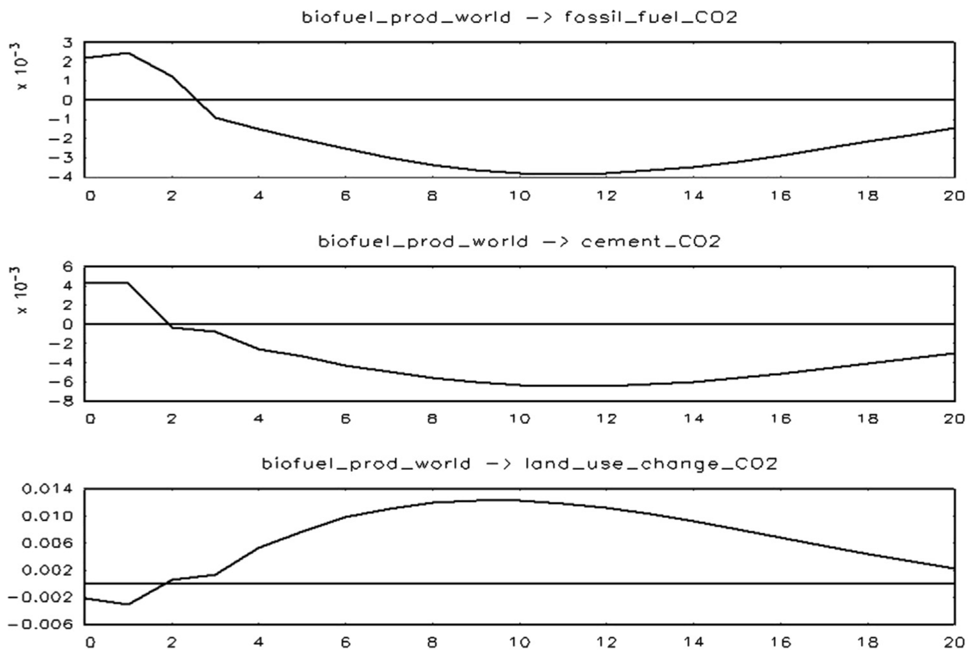

Fig. 3. Impact of an increase in world-wide biofuel production (impulse) of one standard deviation on the global CO_2 emissions (response), by source of emission. *Notes*: *Y*-axis measure million metric tons of CO_2 in natural logarithm, *X*-axis captures years.

Table 3
CO_2 emission elasticities with respect to the world biofuel production.

Emission type	1 year	5 years	10 years	15 years	20 years
Aggregated CO_2 emissions					
Global CO_2 emissions	0.57	−0.40	−0.63	−0.80	−0.57
CO_2 emissions by emission source					
Fossil fuel CO_2 emissions	1.37	−1.20	−2.17	−1.83	−0.80
Cement CO_2 emissions	2.40	−1.89	−3.60	−3.20	−1.71
Land use change CO_2 emissions	−1.71	4.40	7.03	4.57	1.26

Notes: Response of CO_2 emissions in billion metric tons to positive shock in biofuel production (1 million gallon).

The land use results imply that biofuels induce expansion of agricultural land to new areas leading to a release of carbon, which was stored in the forest, soil and/or peat layers [34,16,17,5,29,33]. The dynamics of the estimated land use change effect on CO_2 emissions is non-linear. The emissions are around zero (from slightly negative to slightly positive) in first 3 years. This initial small change in CO_2 emissions can be explained by the fact that the conversion of forest and fallow land for agricultural cultivation is not instant and requires undertaking investments from the side of farmers (e.g. cleaning land; extra machinery). In contrast, CO_2 emissions from deforested land are released over a longer period of time. The emissions from land use change stabilise around 8–12 years after the biofuel shock, followed by a slight decrease in the impact. However, as explained above, the implications of long-run results (>15 years) should be interpreted with care.

4.4. Elasticities of CO_2 emission with respect to biofuels

The estimated coefficients in the cointegrating equation allow us to calculate long-run CO_2 emission elasticities with respect to the world biofuel production. Given that both variables are in natural logarithms, the coefficient estimates can be directly interpreted as elasticities. The estimation results expressed in the form of elasticities are reported in Table 3.

In line with the results reported in the previous section, the estimated elasticities for the aggregated global CO_2 emissions suggest that biofuels increase CO_2 emissions in the short-run, but reduce them in the medium- to long-run. The medium- to long-run CO_2 emission elasticities with respect to the world biofuel production range between −0.80 (15 years) and −0.57 (20 years) (first numerical row in Table 3).

The estimated elasticities for the disaggregated results by the source of emission are reported in the last three rows in Table 3. In line with the results reported in Fig. 3, in short-run they are positive for fossil fuel emissions and cement emissions, whereas negative for land use change emissions. In contrast, in the medium- to long-run they are negative for fossil fuel emissions and cement emissions, whereas positive for land use change emissions.

5. Conclusions and policy implications

An often used argument for supporting biofuel is its potential to lower greenhouse gas emissions compared to those of fossil fuels. The extent to which biofuels lower greenhouse gas emissions compared to those of fossil fuels depends on many factors, some of which are more obvious (direct effects), whereas others are less visible (indirect effects). An example of the former is the production method and the type of feedstock used. An example of the latter is the indirect land use change, which have potential to cause even more emissions than what would be caused by using fossil fuels alone.

Theoretical literature has identified several channels through which a rise in bioenergy can increase CO_2 emissions (indirect land use change, carbon leakage, and crop yield effect), as well as several channels through which a rise in bioenergy can reduce CO_2 emissions (fuel substitution effect and consumption effect). Depending on the relative strength of the different channels of adjustment, an increase in bioenergy production/consumption can affect CO_2 emissions either positively or negatively.

Two types of approaches are used in the empirical literature to assess the impact of additional biofuel production on CO_2 emissions: Life Cycle Assessment (LCA) analysis and Computable General (and Partial) Equilibrium (CGE) models. Both types of models suffer from drawbacks, which limit their helpfulness for policy makers. For example, whereas most of the LCA models do not consider the induced indirect effects, PE and CGE simulation models suffer from their sensitivity to calibrated parameters.

The present study attempts to fill this research gap and to estimate the environmental impacts of biofuels, by explicitly addressing the above mentioned weaknesses of both the LCA and CGE studies. First, by employing a structural vector autoregression approach, where all variables can be modelled as endogenous, we are able to account for all direct and induced indirect effects. Second, by estimating the underlying structural parameters on reasonably long time-series data econometrically, we are able to ensure sufficiently high empirical predictive performance of our results.

We find that in the medium- to long-run biofuels significantly reduce global CO_2 emissions. The estimated global CO_2 emission elasticities range between -0.57 and -0.80. In the short-run, however, biofuels may increase CO_2 emissions temporarily (elasticity 0.57). Our findings complement those of life-cycle assessment and simulation models. However, by employing a more holistic approach and obtaining more robust estimates of environmental impact of biofuels, our results are particularly valuable for policy makers.

Our findings are highly important for policy makers, as they help to better understand the role of biofuels in determining their impact on CO_2 emissions. Our results indirectly confirm that biofuels may lead to indirect land use changes. However, the overall effect of biofuels seems to be a reduction in the total CO_2 emissions in the long run. Other channels offset the effect of indirect land use changes. These results suggest that policies, which stimulate biofuel production (which is the case of many developed countries), have positive environmental consequences and/or positive climate change impact leading to less CO_2 emissions in the long run. Hence, our findings contradict studies, which find that biofuels induce more emissions than fossil fuels (e.g. [30,36]).

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