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Predicting structural changes of the energy sector in an input–output framework

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ABSTRACT

The share of renewable energies has to increase significantly in the ongoing energy transition. Such a shift in production technology is expected to have noticeable effects on the energy sector's input structure that is required for its output. This study examines how changes in a country's energy mix affect its energy sector's input coefficients within an input–output framework, using Austria's *renewable expansion act* as a case study. Predicting input coefficients can be time-consuming and often relies on trends in past data. Our empirical approach is based on a fractional econometric model using panel data on the energy mix and input structures of energy sectors for 26 European countries, and can be efficiently and readily applied to the 26 countries covered in the model. We illustrate the prediction of input coefficients for Austria's energy sector in 2030. We find that input shares from the energy sector to itself would remain high, while mining inputs would decrease. Our model also predicts that increasing the share of renewable energy sources comes with a significant decrease in the share of labor inputs, mainly because operating renewable energy technologies requires less labor than operating non-renewable ones. The presented method allows to assess renewable energy policy plans to anticipate the effects of structural changes in national energy sectors.

1. Introduction

In 2021, Austrian policy makers passed the so-called *renewable expansion act*, which aims at increasing national energy production from renewable sources by 27 terawatt-hours (TWh) [1]. By investing approximately one billion euros per year until 2030 via market bonuses and investment subsidies, the bill targets solar (+11 TWh), wind (+10 TWh), hydro power (+5 TWh) and biomass (+1 TWh) as part of the package.

Research suggests that subsidies can leverage substantial investment in renewable energy sources [2–4]. But it remains unknown how the input structure of the Austrian energy sector[1] would look like in the case that the bill fulfills its purpose. Predictions of future input coefficients can be helpful in a number of applications, as input–output structures are employed in many economic models and are also frequently used to assess economic, social, and environmental effects of policies. In our case, the predicted structural change can be used to assess the effects of alternative policies before a renewable expansion law is passed.

To answer this question and to address this research gap, we present a novel approach for modeling the input structure of the energy sector, assuming that the targeted energy mix[2] is reached by 2030. Using the *Fractional Multinomial Logit* (FMNL) model and panel data on input coefficients and energy mixes of 26 European countries and comparing the predictions to the related literature, we show that our method is a reliable and efficient approach in predicting future input coefficients, which can also complement existing methods and can be used to disaggregate sectors. We find that the Austrian energy sector would undergo major changes: While demand for inputs from the energy sector itself would remain high, our results suggest that labor and mining inputs would decrease significantly. The marginal effects of our model indicate that changes in the input structure are driven by a combination of increasing the share of renewable energy sources that require less labor and, conversely, reducing the share of labor-intensive non-renewable energy sources in the energy mix.

As all member states of the European Union have agreed to cut greenhouse gas (GHG) emissions by 55% until 2030 [5], other EU

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[1] For better readability, we use the term *energy sector* for NACE Rev. 2 sector D35 (see Section 3.1.1).

[2] In this study, the term *energy mix* refers to the shares of energy products used for the production of electricity and steam (heat) in NACE Rev. 2 sector D35.

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countries will very likely also implement policies that target major transitions in national energy sectors. With our novel and time-efficient approach being readily replicable and applicable to 26 European countries, we provide policy makers and scholars with a tool that allows to anticipate and adapt to possible future developments in national energy sectors before implementing major policy interventions.

2. State of research

In input–output statistics, the current production technology is represented by technical and primary input coefficients [6]. While the first describe the inputs per unit received from other sectors, the latter represent value added per unit, i. e., the costs per unit for wages, production taxes less subsidies, depreciation and profits.

In the short term, it is assumed that these coefficients are quite stable. In the long run, this is usually not the case. Using energetic building retrofits as an example, Hartwig and Kockat [7] show that the technology and thus the input–output tables used can have considerable effects on the estimation of economic impacts.

There are multiple options to project technological change in an input–output framework. One option is to use trend analysis to extrapolate coefficient changes from historic data into the future, e. g., by describing technology penetration by logistic growth curves. While this approach is rather simple from a methodological point of view and the required data are usually readily available, it suffers from the major disadvantage that it is conceptually impossible to predict fundamental technological changes from past trends. The second option, according to Faber et al. [8], is to predict future coefficients based on expert judgement. This can be done by relying on engineering data or experts' assessments of the change of technical coefficients relative to a base year. This method yields more realistic results, especially in the case of fundamentally different technologies, but is rather labor intensive and data might not be available or reliable.

Pan [9] proposed a dynamic input–output model, which includes endogenous technical progress and deployment. Coefficients in this model change from an old to a new set of technologies over time, depending on investment in research and development and in the capital stock. In another study, Pan and Koehler [10] apply this approach to wind power in the UK. Gurgul and Lach [11] develop a similar model to forecast the inter-industry linkages of sectors in the Polish economy. Hartwig et al. [12] combine bottom-up energy demand models with an input–output based macroeconomic model and apply it to energy efficiency policy options in Germany. In the scenario approach applied by Wiebe et al. [13] specific elements of the input–output system are manually adjusted according to exogenously given scenario specifications. Among others, these include adaptations of final demand for renewable energies and corresponding investments as well as technical and primary input coefficients of the relevant sectors. Faber et al. [8] and Wilting et al. [14] combine trend analysis and detailed information on specific technologies to adjust coefficients and evaluate the effects of technological change on Dutch production and air emissions.

In the national accounts and in input–output statistics (such as the FIGARO tables used in this study) sectors are usually represented as aggregates and may include heterogeneous activities, which can lead to a considerable aggregation bias. As Lenzen [15] points out, using disaggregated data is usually superior, even if based on few real data points. As technical change in the electricity sector currently mostly resembles shifts between production technologies from fossil electricity generation towards renewables, disaggregated generation technologies can also help to account for technological change within the energy sector. This disaggregation can be done by determining the input coefficients for the relevant technologies based on expert judgement and engineering data [16]. Examples include Vendries Algarin et al. [17] for the U.S., Duarte et al. [18] for Spain, Allan et al. [19] for Scotland, Wolfram et al. [20] for Australia and Wiedmann et al. [21] for wind power in the UK. The latter two studies combine input–output data with process data from life cycle databases in hybrid Life Cycle Assessment methods to estimate carbon footprints for individual electricity generation technologies. These approaches, however, require extensive research on the most relevant production technologies involved.

A model specifically designed to allow for different technologies within an industry is the rectangular choice-of-technology (RCOT) model [22–24], which uses rectangular tables with potentially multiple columns, i. e., production technologies, per industry, and enables constraints regarding the availability of primary inputs. A linear programming technique is used to find the optimal mix of production. Kätelhön et al. [25] combine the RCOT model with consequential life cycle assessment and stochastic elements.

Some input–output databases like EXIOBASE [26] or the GTAP-Power Data Base [27,28] already provide specific coefficients for various electricity generation technologies, but not all sectors and coefficients are empirically validated.

As a complementary and time-efficient approach, we propose to predict future input coefficients of the energy sector using econometric methods and panel data, as described in the following sections. We argue that our approach comes with several advantages compared to the other methods presented in this section, as it can be readily applied to a large set of countries and does not rely on expert judgements. Moreover, our method is more flexible than a trend analysis based on a single country, as our econometric model also captures the information about technological changes that already occurred in other countries. The method can also be used to disaggregate the energy sector and help to cross-validate, triangulate, and thereby corroborate predictions resulting from the other methods.

3. Data and methodology

3.1. Description of variables

We use Eurostat [29,30] data to derive the input coefficients (dependent variables) and the energy mix (independent variables) for our econometric model. Our final data set consists of 285 observations. For every year[3] from 2010 to 2020 it contains observations for all EU-28 countries except Malta and Cyprus, which we exclude due to data issues.

3.1.1. Input coefficients

The variables of interest in this study are input coefficients derived from the *Full International and Global Accounts for Research in Input–Output analysis* (FIGARO) provided by Eurostat [30]. These tables connect all EU-27 countries, 18 main trading partners, and the rest of the world as an aggregate unit at a detailed level of 64 industries. Industries, also often referred to as sectors, are structured according to NACE Rev. 2 [31].

In our analysis, we focus on the relative monetary shares of the inputs and value added of sector D35, officially designated as *'electricity, gas, steam and air conditioning supply'*, which is, for better readability, referred to as the *energy sector*, *sector D35* or *sector D* in this study.

As the number of predictable input sectors is constrained by the number of observations in our data set, we aggregate the 64 available input sectors to a total of 32 input sectors plus two separate value added components[4] (see first column in Table 1 for the aggregate sectors). *Labor value added* (VA-L) contains labor inputs; *Rest value added* (VA-R) contains all other value added components, such as depreciation and

[3] Except for the UK in 2020, for which no energy mix data was available yet.

[4] Input coefficients do not include inputs required for investments, which are considered as final demand. Depreciation for investments is taken into account as a part of value added.

Table 1
Input coefficients of the Austrian energy sector in percent.
Source: [30].

Sector(s)	Name	2010	2020	Difference
A	Agriculture	0.22	0.23	0.01
B	Mining	3.85	3.39	−0.46
C10–12	Food, beverages and tobacco	0.08	0.05	−0.03
C13–15	Textiles, apparel and leather	0.02	0.01	−0.01
C16–18	Wood, paper and printing	0.43	0.25	−0.18
C19	Coke and refined petroleum	0.79	0.30	−0.49
C20–21	Chemicals and pharmaceuticals	0.15	0.13	−0.02
C22–23	Rubber, plastic, non-metallic minerals	0.31	0.20	−0.11
C24–25	Basic and fabricated metals	0.56	0.33	−0.23
C26	Computers, electronics and opticals	0.16	0.07	−0.09
C27	Electrical equipment	1.64	0.35	−1.29
C28	Machinery and equipment	0.39	0.27	−0.12
C29–30	Motor vehicles and other transport equipment	0.06	0.05	−0.01
C31–33	Furniture, other manuf., repair and installation	1.17	0.88	−0.29
D	Energy	53.82	62.97	9.15
E	Water supply, waste and sewerage	1.55	1.39	−0.16
F	Construction	1.12	1.00	−0.12
G	Wholesale and retail trade	1.75	1.85	0.10
H	Transport and storage	2.80	1.97	−0.83
I	Accommodation and food service	0.62	0.39	−0.23
J58–60	Publishing, motion picture, music and broadc.	0.09	0.07	−0.02
J61	Telecommunications	0.19	0.12	−0.07
J62–63	Information technology	0.50	0.43	−0.07
K	Finance and insurance	2.13	2.39	0.26
L68	Real estate	0.37	0.36	−0.01
M	Professional, scientific and technical activities	1.49	1.06	−0.43
N	Administrative and support service activities	0.81	1.39	0.58
O84	Public administration, defense and social security	0.14	0.21	0.07
P85	Education	0.29	0.13	−0.16
Q	Human health and social work	0.02	0.02	0.00
R-S	Arts, entertainment, recreation and other services	0.05	0.04	−0.01
T-U	Households and extraterritorial organizations	0.00	0.00	0.00
VA-L	Labor value added	8.03	7.75	−0.28
VA-R	Rest value added	14.42	9.95	−4.47
Total	Sum of all sectoral and value added components	100.00	100.00	0.00

operating surplus. VA-L and VA-R together form the residual between total input and intermediate input from other sectors.

In addition, the aggregation of import and domestic input sectors is necessary for computing technical input coefficients. This aggregation step comes with the disadvantage that our model cannot take trade into account separately and treats all inputs (whether domestic or imported) as the same (see, e. g. Wiebe et al. [13],Wolfram et al. [20],Wiedmann et al. [21], who face similar restrictions). As a last step, we convert the values to shares, which add up to 1. Table 1 shows the input coefficients of the Austrian energy sector in the first (2010) and in the last year (2020)[5] of the panel. Moreover, the change between the years is shown in the 5th column. For better readability, the coefficients are multiplied by 100. As can be seen in the table, most inputs came from the energy sector (D) itself; this input also showed the highest increase between 2010 and 2020. Gross value added, especially the non-labor residual VA-R, decreased substantially. The mining (B) and manufacturing (C) sectors all showed a decrease as input providers between 2010 and 2020.

3.1.2. *Energy mix*

As our analysis targets sector D35 as a whole, the energy mix captured by our independent variables has to cover energy used for the production of both electricity and steam (heat). Data for the energy mix comes from the Eurostat [29] *Energy Statistics Database*. We use information from the variables *nrg_ind_peh* and *nrg_ind_pehcf* on gross production of electricity and heat by main producers for each energy product.[6]

We aggregate the data, which has been published in *Standard International Energy Product Classification* [32], to the ten most important energy products in our data set. The rest contains energy from geothermal sources, tide, wave, ocean, ambient heat (heat pumps) and heat from chemical sources.

The 2nd and 3rd column of Table 2 show the energy mix for Austria for 2010 and 2020. The most important energy product for Austria is (pumped) hydro power, which approximately made up half of the energy mix in both years, followed by natural gas and liquid and solid biofuels, whereas the other seven energy products only make up small fractions of the mix. As can be seen in the 4th column, a decrease in the share of non-renewable combustible energy products can be observed, which was offset by an increase in renewable energy production.

For predicting the Austrian input coefficients in 2030, we calculate an energy mix target for 2030, which is shown in the 6th column of Table 2. We derive this target by adding the planned 27 TWh increase (5th column) to the energy mix of 2020, which was the most recent data available.

3.1.3. *Control variables*

We introduce three additional control variables in our model. We use terajoules of final consumption of natural gas[7] [29,33, variables*nrg_cb _gas, demo_pjan*] for energy use to account for the gas sector

[5] We did not find any noticeable differences in the input coefficients between the years 2019 and 2020 (outbreak of the SARS-Cov-2 virus and following supply chain disruptions in many sectors).

[6] In this study, we use the terms *energy product*, *energy source* and *energy (production) technology* interchangeably, as they all can be connected to our explanatory variables.

[7] In our prediction we assume consumption in Austria to remain unchanged between 2020 and 2030, as it remained nearly constant between 2010 and 2020.

Table 2
Energy mix of the Austrian energy sector for selected years.
Source: [29].

Energy product Unit	2010 %	2020 %	Δ '10-'20 %-points	Increase TWh	Target 2030 %
(Pumped) hydro	49.92	52.65	2.73	5	44.44
Wind	2.54	7.96	5.42	10	14.95
Solar	0.13	2.43	2.30	11	11.64
Coal and peat	6.71	0.97	−5.74	0	0.74
Natural gas	23.80	18.75	−5.05	0	14.24
Oil and shale	2.46	0.21	−2.25	0	0.16
Biogas	0.82	0.69	−0.13	0	1.41
Liquid and solid biofuel	11.71	13.51	1.80	1	10.26
Nuclear	0.00	0.00	0.00	0	0.00
Other	1.91	2.84	0.93	0	2.16
Total (TWh)	81.13	85.28	4.15	27	112.28

within NACE sector D35. GDP per capita [34, variable *nama_10_pc*] expressed in purchasing power standards[8] controls for general differences in productivity between countries and years. Absolute size of the energy sector expressed as TWh of production of heat and electricity by main producers [29] allows us to make assumptions about the future size of the energy sector. With this variable, the (non-linear) relations between sector size and input fractions can be predicted.[9] Once sector size is converted into total output, the fractions can also be transformed into absolute values of the sector within the input–output tables of an economy, and the accounts can be balanced [37].

Additionally, we introduce dummy variables for years and countries to control for any unobserved country- and year-specific characteristics. These other characteristics capture differences and changes (between countries and/or years) in input prices, geographical and annual climate conditions, country-specific productivity, and economic development, among others.

In our model, we use Austria and the year 2020 as the baseline categories. By doing so, we essentially assume that unobserved characteristics in 2030 were the same as in 2020. We argue that the year 2020, which was our most recent year in the data set, is our best predictor for unknown year-specific characteristics in 2030. Please note the limitation that some of these unobserved characteristics, such as climate conditions, are highly likely to change between 2020 and 2030, whereas our model assumes year-specific characteristics of 2020 to be persisting also in the future.

3.2. Fractional multinomial logit model

We want to model the jth input coefficient of the energy sector in a specific country and a specific year $\mathbf{Y}_i$ as a function of the energy mix and other characteristics $\mathbf{X}_i$ of the same year and country. We also have to consider all input coefficients $\mathbf{y}_{i,-j}$, excluding the coefficient of interest itself. This can be formally written as

$$y_{ij} = f(\mathbf{X}_i, \mathbf{y}_{i,-j}) \tag{1}$$

, where $f(\cdot)$ is some function of yet unknown form. Because of the nature of our problem we need some model that both ensures that $0 \leq y_{ij} \leq 1$ and $\sum_{m=1}^{M} y_{im} = 1$, where M is the number of input coefficients.

We estimate the relationship in (1) using the *Fractional Multinomial Likelihood* (FMNL) method. It is the multinomial generalization of research by Papke and Wooldridge [38], who proposed an econometric method for binary fractional response variables via *Quasi-Maximum-Likelihood estimation*; for an excellent comprehensive overview of fractional regression models, see Ramalho et al. [39]. These models have been applied in a variety of studies, including the analysis of enterprise financing in transition economies [40], industrial organization [41], or the estimation of national energy ladders [42] and Engel Curves [43], and have also been proposed in relative efficiency evaluation [44], among others.

The essential feature of the FMNL method is that it allows to estimate not only one but M dependent variables, which are estimated simultaneously. Another feature is that for each observation i the ys are bound between 0 and 1 and sum up to 1. The ys of an observation can also be interpreted as fractions. As this is also true for input coefficients, FMNL is an ideal method for the purpose of our study. Note that Eqs. (2) to (5) below are obtained from literature by Papke and Wooldridge [38], Ramalho et al. [39] and Wulff [45].

Assume we have I observations and

$$E(y_{ij}|\mathbf{X}_i) = G(\mathbf{X}_i\beta_j) \tag{2}$$

where y_{ij} is the jth fraction of the ith observation. $\mathbf{X}_i$ is the vector of K independent variables and β_j the vector containing K regression coefficients. Note that for every fraction $m = 0, \dots, M$, there is one set of K coefficients.

$G(\cdot)$ is some function satisfying $1 < G(z) < 0$ for all $z \in \mathbb{R}$. For binary response variables, the logistic function is an obvious choice for $G(\cdot)$ [39]; for multinomial applications, the equivalent is the multinomial logit function. Usually, one fraction is treated as the baseline. Assume we select the first fraction as the baseline,[10] which implies $\beta_1^{\top} = (0, 0, 0, \dots, 0)$ and

$$G(\mathbf{X}_i\beta_j) = \frac{exp(\mathbf{X}_i\beta_j)}{\sum_{m=1}^{M} exp(\mathbf{X}_i\beta_m)} = \frac{exp(\mathbf{X}_i\beta_j)}{1 + \sum_{m=2}^{M} exp(\mathbf{X}_i\beta_m)}. \tag{3}$$

The corresponding multinomial likelihood function is

$$ln(L_i) = \sum_{m=1}^{M} y_{im} ln(G(\mathbf{X}_i\beta_m)). \tag{4}$$

We use the quasi-maximum-likelihood estimator from

$$\hat{\beta}_m = \arg\max_{\beta_m} \sum_{i=1}^{I} ln(L_i) \tag{5}$$

as it is a consistent estimator for β_m if our choice for $G(\cdot)$ is indeed the true functional form, as shown by Papke and Wooldridge [38].

Interpretation of coefficient estimates of FMNL models is not straightforward, as for every independent variable $\mathbf{X}_k$ there are M marginal effects (ME). ME statistics that have a similar interpretation as the coefficients of continuous variables in a classical linear model (ME $= \delta\mathbf{y}/\delta\mathbf{X}$) can be derived from the estimates. For a summary of the most important ME statistics and their interpretation, see Wulff [45].

Estimations were performed in Stata [46], using the fmlogit-module by Buis [47]. Standard errors were clustered by countries.

3.3. Workflow summary

Fig. 1 gives an overview of the steps described in Section 3. First, (1) data is obtained from Eurostat databases, then (2) subsetted, filtered, and transformed for (3) being used as the dependent, independent, control- and dummy-variables. Data is then (4) merged by country and year and observations with bad data quality are removed manually. The resulting (5) data set, consisting of 285 observations, is then passed to the (6) FMNL model, which yields the (7) coefficient estimates. These can be used to (8, 9) derive marginal effects or, when (10) making certain assumptions, to (11) forecast (12) input coefficients of the Austrian energy sector, (13) perform sectoral disaggregations and (14) in-sample predictions.

[8] We assume a growth in GDP per capita of 15% between 2020 and 2030 in Austria for our prediction, as projected by the OECD [35,36].

[9] We assume a sector size of 112.28 TWh of production in Austria, see Table 2.

[10] For our application, this is sector D.

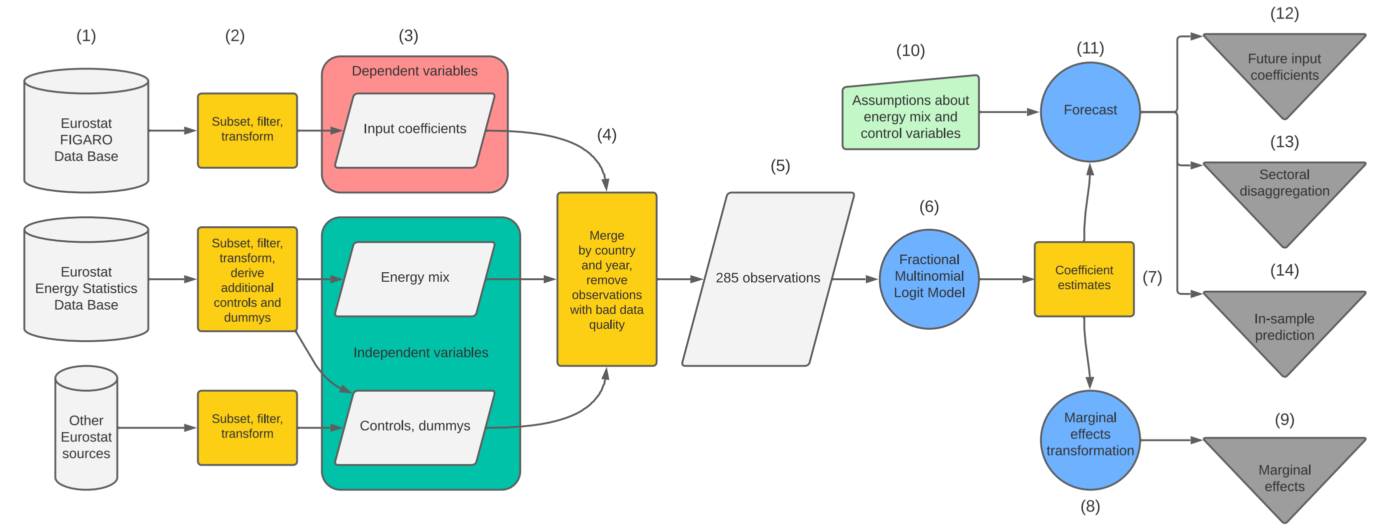

Fig. 1. Workflow summary.

4. Results and discussion

4.1. Predictive power of the model

Before we discuss the actual FMNL estimation results, we take a look at how well the model fits our data and how the targeted energy mix affects the predicted input coefficients of the Austrian energy sector in 2030. Fig. 2 shows these input coefficients. White columns are the historical values as of 2010, while light gray columns depict current values in 2020, and the black columns represent the fitted values for 2020 using our FMNL model and the energy mix of 2020. We do not observe sizable differences between the actual and estimated coefficients for any of the sectors, which indicates that our model provides a reasonable fit for the response variables at hand. Fig. A.1 in the Appendix provides additional metrics on prediction quality for selected sectors.

By using the target energy mix for 2030, we are now able to predict the future input coefficients of the Austrian energy sector. These are represented by the blue columns in Fig. 2. We observe notable differences compared to 2020 only for a few sectors. We will in the following focus on sectors whose predicted input shares in 2030 turn out to be significantly different from their 2020 shares (at the 90% level) and are at the same time among the ten sectors with predicted input shares of at least 1% and can therefore be considered economically relevant for the energy sector. This would leave us only with the mining sector (B) and labor (VA-L). In addition, we will show and discuss the energy sector itself (D) as it continues to provide about two thirds of its inputs.

We see a continuing decrease for the mining sector (B). Its input coefficient decreases as energy production shifts from carbon-based to renewable sources. Inputs from the energy sector itself (D) continue to make up the highest share of all inputs. The slight increase of input coefficients from D is in line with the pattern for Austria over the last years, but statistically insignificant (as indicated by the error bars in Fig. 2). The labor share (VA-L), on the other hand, is expected to decrease substantially, as electricity generation from renewable energy sources such as wind or solar power generally comes with lower or almost zero marginal costs (see, e. g. Blazquez et al. [48]).

4.2. Austria's renewable expansion act

In the following, we present FMNL estimation results for the three selected sectors to allow for a detailed analysis of the predictions presented above. Coefficients of FMNL models[11] are hard to interpret. As we have presented predictions for Austria before, we focus now on marginal effects at the Austrian energy mix in 2020. We will first show marginal effects and then explain what they mean in the context of the Austrian renewable expansion act and the changing energy mix until 2030. Table 3 presents the results for the three selected sectors.

Table 3
Marginal effects.

Labor (VA-L)	dydx	std. err.	p-value
Hydro	−0.3719	0.2493	0.136
Wind	−0.5453**	0.2759	0.048
Solar	−0.6545***	0.2531	0.010
Coal	−0.4526*	0.2517	0.072
Gas	−0.4173*	0.2360	0.077
Oil	−0.4189*	0.2382	0.079
Liquid and solid biofuel	−0.3039	0.2365	0.199
Biogas	0.1606	0.3561	0.652
Nuclear	−0.4081	0.2482	0.100
Energy (D)	**dydx**	**std. err.**	**p-value**
Hydro	2.3229**	1.1371	0.041
Wind	2.7090**	1.2369	0.029
Solar	2.7931***	1.0676	0.009
Coal	2.4582**	1.1481	0.032
Gas	2.4521**	1.0909	0.025
Oil	2.3449**	1.0836	0.030
Liquid and solid biofuel	2.0020**	1.0186	0.049
Biogas	1.7240	1.8041	0.339
Nuclear	2.1323*	1.1524	0.064
Mining (B)	**dydx**	**std. err.**	**p-value**
Hydro	−0.0821	0.1622	0.613
Wind	−0.2174	0.1651	0.188
Solar	−0.0377	0.1618	0.816
Coal	−0.0836	0.1578	0.596
Gas	−0.1097	0.1614	0.497
Oil	−0.0633	0.1476	0.668
Liquid and solid biofuel	−0.0390	0.1524	0.798
Biogas	−0.1917	0.2607	0.462
Nuclear	−0.0461	0.1584	0.771

$^{*}p < 0.1$.
$^{**}p < 0.05$.
$^{***}p < 0.01$.

11 Tables of raw FMNL coefficients are available from the authors upon request.

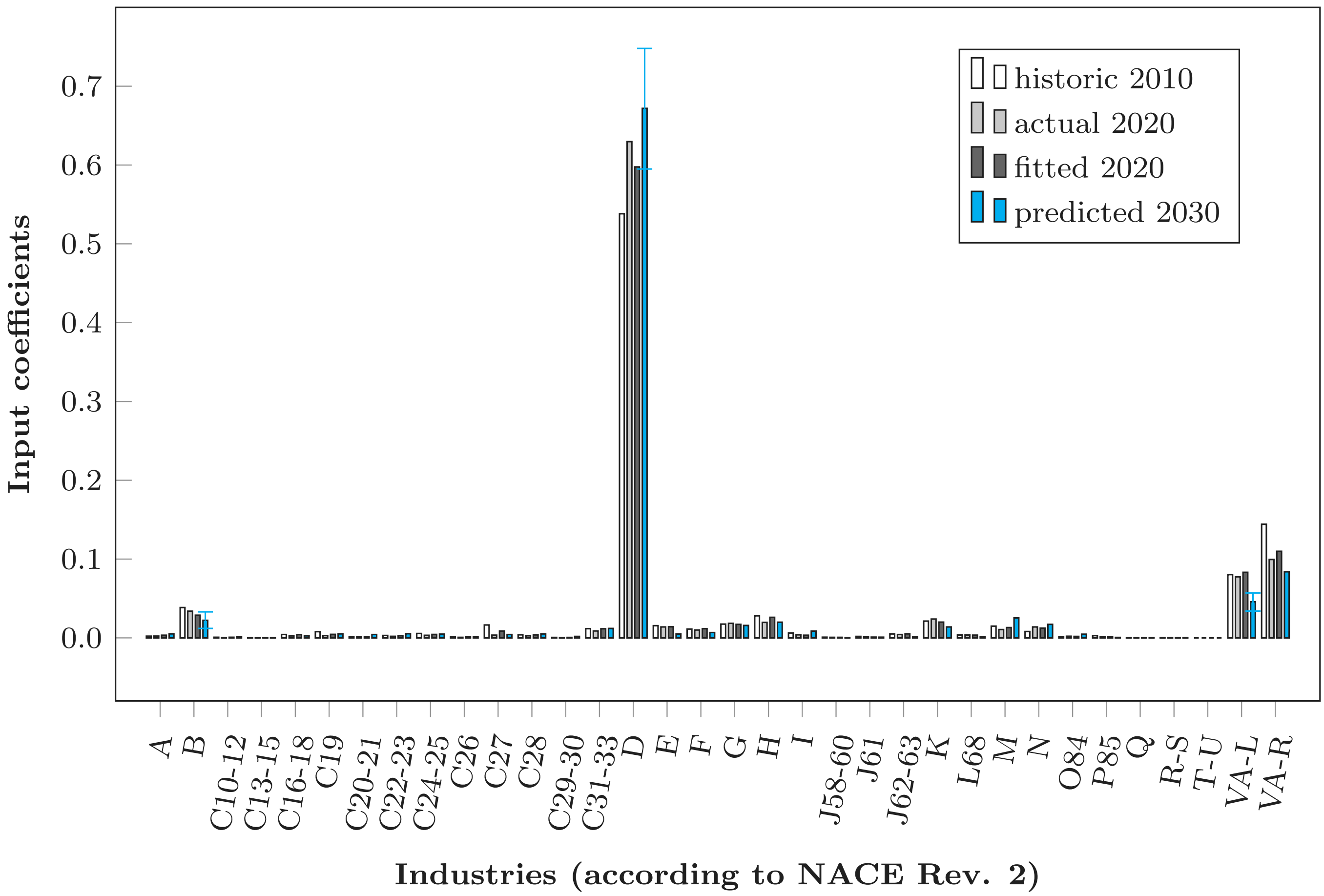

Fig. 2. Input coefficients (historic 2010 vs. actual 2020 vs. fitted 2020 vs. predicted 2030) of Austria's energy sector. Error bars indicate confidence intervals at the 90% threshold for the three selected sectors' 2030 predictions. B and VA-L are significantly different from 2020 values; D is not. All other sectors are either insignificant and/or predicted to be below 1%.

Most of the marginal effects for the labor share (VA-L) are negative and statistically significant. This finding might at first not seem particularly intuitive as any kind of energy production should require some amount of labor and thus produce value added. What is more important, however, is the net effect: An increase in the contribution of one energy source to the energy mix must come with a decrease in another. The interesting feature here is that solar power stands out, as it shows the largest marginal effect (in absolute terms). If the share of solar power in the energy mix is increased by 1 percentage point (pp), this would come with a decrease of the labor share of 0.65 pp. As this must be offset by a reduction in the share of at least one other energy source by 1 pp, the net effect must be negative as all other coefficients are greater than −0.65. If, for example, solar replaces coal, the net effect is −0.20. Would it replace oil or gas, the net effect would be −0.24. This explains the decline of our predicted labor share for 2030 in Fig. 2. As Austria is going to massively increase its solar share and therefore reduces the relative share of many other energy sources in its energy mix, its labor share is predicted to drop by more than 3 pp until 2030. Similar but smaller effects apply for wind power.

All marginal effects for the energy sector's (D) input shares show positive values and most of them are statistically significant. This implies that most changes in the energy mix will have some impact on the share of inputs provided by the energy sector. Again, solar and wind power show the largest marginal effects. If solar power gains weight in the energy mix, this would come with an increase of the input share of sector D. As any other energy source has to be reduced accordingly in the energy mix, the net effect must be slightly positive, as all other coefficients are smaller than 2.8. This phenomenon explains the small increase in the Austrian energy sector's input share for 2030 in Fig. 2 (compared to the actual value of 2020). Behind this result is the fact that companies of the same sector now interact with one another where companies from different sectors have interacted before. For example: A coal-fired power plant needs inputs from mining, manufacturing, etc., and will also have to pay, e. g., transmission fees to other companies of its own sector (D). An existing wind park of the same capacity, on the other hand, does not require large amounts of inputs from other sectors for its operation. Hence, transmission fees now make up for a larger share of inputs.

The marginal effects for the mining sector's (B) inputs to the energy sector are negative. It must be noted, though, that all of them are very small and statistically insignificant. Still, the interpretation logic would be the same as above. An increase in the share of one energy source would come with a decrease of the share of another energy source. The largest marginal effect (in absolute terms) is for wind energy: If the share of wind in the energy mix increases by 1 pp, the input share from the mining sector would decrease by 0.22 pp. If the fraction of electric energy currently provided by wind was before generated using coal, the net effect would be −0.13. The mining share would always decrease through an increase in wind energy, no matter what it were to replace.

How can these results be interpreted in the context of Austria's renewable expansion act and the planned change in the energy mix until 2030? The main feature of the change in the energy mix is the increase of the shares of renewable energy sources (especially solar and wind energy by about 16 pp in total[12]) and the decrease of the relative contribution of non-renewable energy production (in particular hydro power and natural gas by about 13 pp in total). We find that the increased production from renewable energy sources (especially wind and solar power) and the replacement of fossil-based energy sources comes with smaller input shares from the mining sector and from labor, while slightly increasing the input share from the energy sector itself.

To further consolidate the empirical results of this study, we have added multiple robustness tests. Fig. A.2 in the Appendix compares actual and fitted input shares for the years 2010, 2015 and 2020. We see clearly that our predicted input shares for 2030 follow time trends that have already been observed during the last decade. Figs. A.3 to A.5 in the Appendix provide hypothetical predictions if the aspired shares of hydro, wind or solar power would be 100%, respectively (for 2030, keeping everything else constant). While our results for hydro and wind power seem perfectly plausible, we find rather unlikely input shares for 100% solar power. Hence, this analysis shows the possibility of using our approach to decompose the energy sector according to different energy production technologies, but also its limitations. If the aspired energy is too far out of support of the data, the findings of the 100% predictions cannot be trusted.

5. Conclusion and policy implications

This study proposes a novel approach that allows to predict structural changes in national energy sectors. Input coefficients are explained by the energy mix in a fractional multinomial logit (FMNL) model. We illustrate the model application to evaluate the effects of Austria's renewable energy expansion act and predict the future input coefficients resulting from the policy. An in-sample prediction of input coefficients shows that the model delivers a reasonable fit for the response variables, i. e., the input coefficients of the energy sector. The approach presented in this study allows to use information about fundamental technological changes that already occurred in countries with high renewable energy shares to predict structural changes in other countries. The method is time-efficient and can also complement other methods to predict input coefficients. Moreover, it can be used to disaggregate the energy sector under the condition that this disaggregation is supported by the underlying data on which the model builds.

Prediction results show that Austria's energy sector would obtain slightly more inputs from the energy sector itself if the targeted energy mix was reached in 2030, while inputs from the mining sector and the labor share are expected to decrease significantly. Marginal effects of the model show that the changes in the input structure are mainly driven by the increase in the share of renewable energy sources, which are less labor intensive than non-renewable energy sources.

Our approach is readily applicable to the 26 European countries covered by the model and enables policy makers and scholars to analyze country-specific (renewable) expansion plans. This helps to assess the potential economic, social, and environmental consequences of plans before corresponding acts are passed, for example with the help of input–output models and corresponding impact analyses. The method can also be employed for predicting changes in other sectors, building on sector-specific explanatory variables that are adequate to model and predict their input structures, which could be at the focus of future research.

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[12] Compared to 2020, see Table 2.

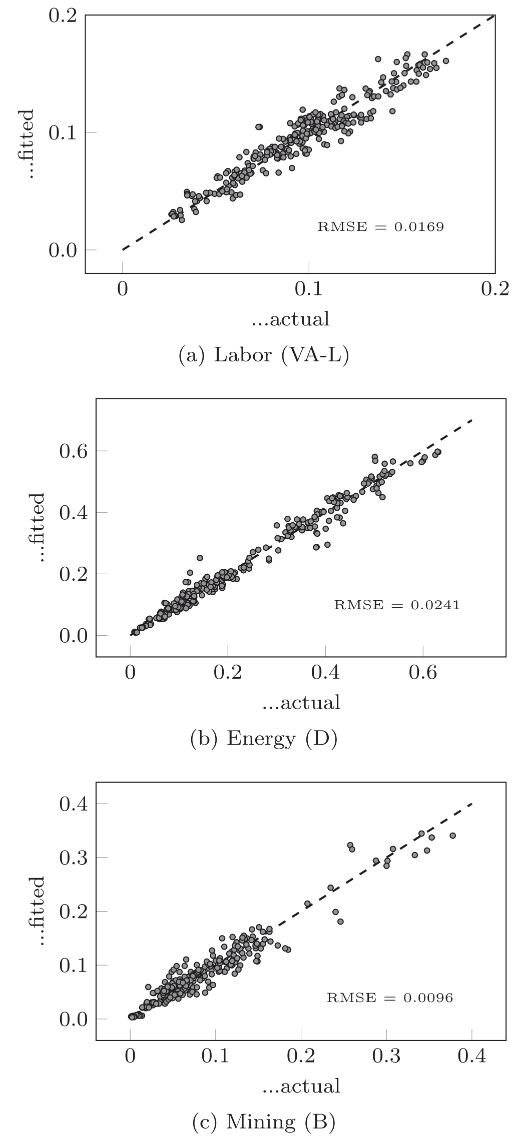

Fig. A.1. Prediction quality (actual vs. fitted input shares).

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: All authors via the research group report financial support was provided by the Austrian Federal Ministry for Climate Action.

Data availability

A data set related to this article and the corresponding R-code to reproduce it can be found at https://github.com/lorenz221092/Predicting_Input_Coefficients. Downloading and transforming the data was performed in R [49] using the `eurostat` [50] and the `tidyverse` [51] packages.

Appendix

See Figs. A.1–A.5.

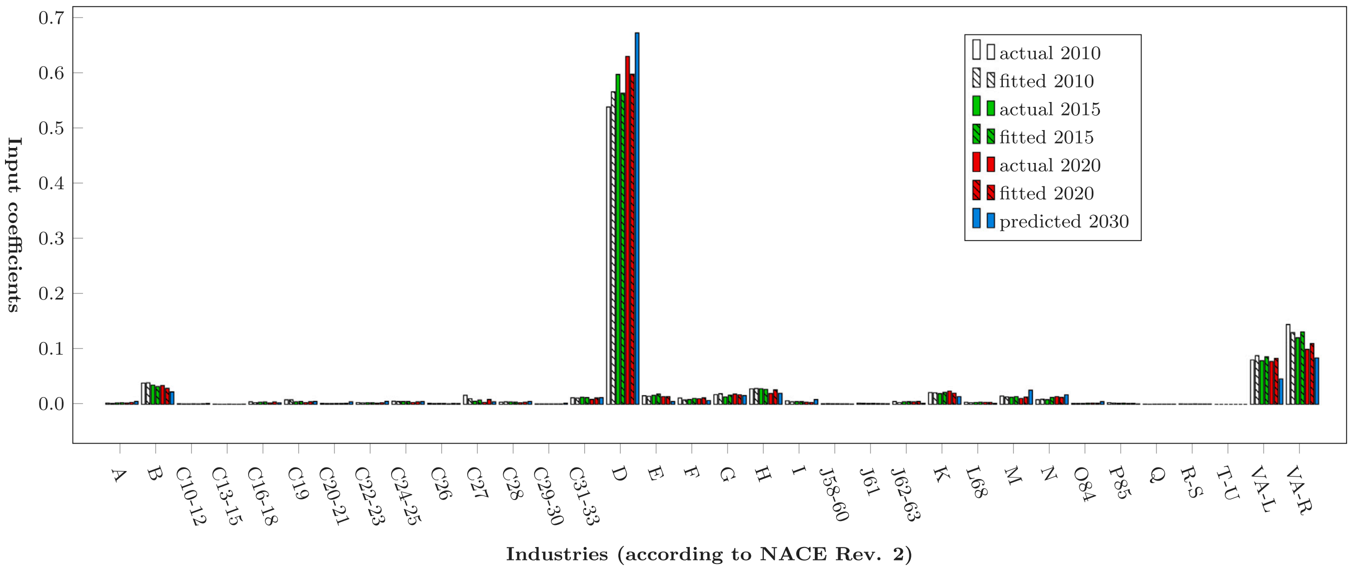

Fig. A.2. Input coefficients (actual 2010, 2015, 2020 vs. fitted 2010, 2015, 2020 vs. predicted 2030) of Austria's energy sector.

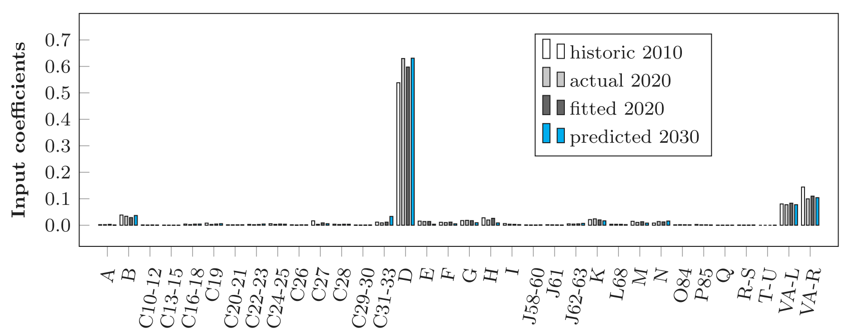

Fig. A.3. Input coefficients of Austria's energy sector (assumption: hydro = 100).

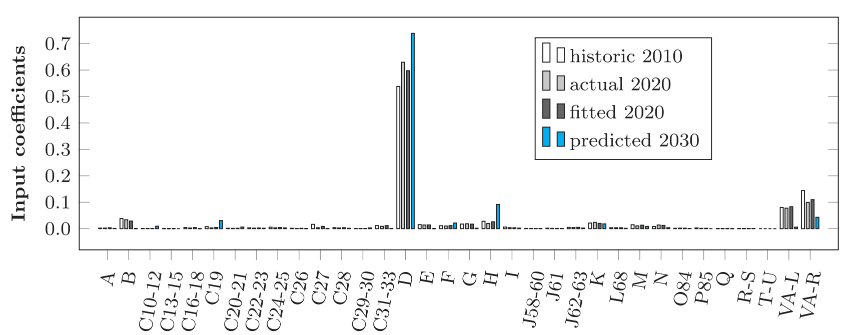

Fig. A.4. Input coefficients of Austria's energy sector (assumption: wind = 100).

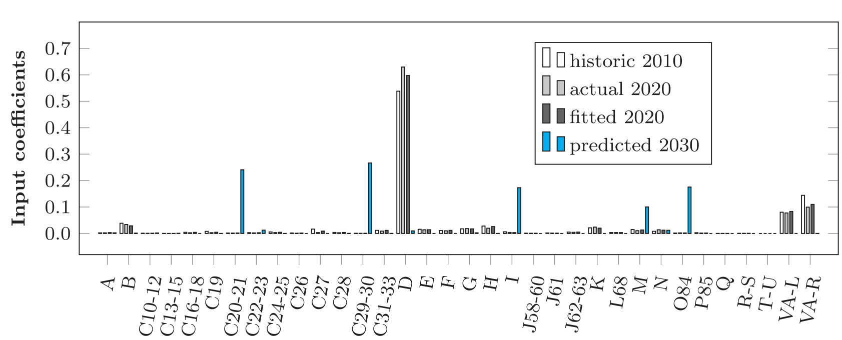

Fig. A.5. Input coefficients of Austria's energy sector (assumption: solar = 100).

References

[1] System LI. Bundesrecht konsolidiert: Gesamte rechtsvorschrift für erneuerbaren-ausbau-gesetz, fassung vom 27.10.2021. 2021, URL: https://www.ris.bka.gv.at/GeltendeFassung.wxe?Abfrage=Bundesnormen&Gesetzesnummer=20011619, [last accessed on 2021/10/27].

[2] Nicolini M, Tavoni M. Are renewable energy subsidies effective? Evidence from Europe. Renew Sustain Energy Rev 2017;74:412–23. http://dx.doi.org/10.1016/j.rser.2016.12.032.

[3] Yang X, He L, Xia Y, Chen Y. Effect of government subsidies on renewable energy investments: The threshold effect. Energy Policy 2019;132:156–66. http://dx.doi.org/10.1016/j.enpol.2019.05.039.

[4] Liu W, Zhang X, Feng S. Does renewable energy policy work? Evidence from a panel data analysis. Renew Energy 2019;135:635–42. http://dx.doi.org/10.1016/j.renene.2018.12.037.

[5] European Commission. 2030 Climate target plan. 2021, URL: https://ec.europa.eu/clima/eu-action/european-green-deal/2030-climate-target-plan_en, [last accessed on 2021/10/27].

[6] Miller RE, Blair PD. Input-output analysis: Foundations and extensions. Cambridge University Press; 2009.

[7] Hartwig J, Kockat J. Macroeconomic effects of energetic building retrofit: input-output sensitivity analyses. Constr Manag Econ 2016;34(2):79–97. http://dx.doi.org/10.1080/01446193.2016.1144928.

[8] Faber A, Idenburg A, Wilting H. Exploring techno-economic scenarios in an input–output model. Futures 2007;39(1):16–37. http://dx.doi.org/10.1016/j.futures.2006.03.011.

[9] Pan H. Dynamic and endogenous change of input–output structure with specific layers of technology. Struct Change Econ Dyn 2006;17(2):200–23. http://dx.doi.org/10.1016/j.strueco.2005.05.003.

[10] Pan H, Koehler J. Technological change in energy systems: Learning curves, logistic curves and input–output coefficients. Ecol Econom 2007;63(4):749–58. http://dx.doi.org/10.1016/j.ecolecon.2007.01.013.

[11] Gurgul H, Lach Ł. Simulating evolution of interindustry linkages in endogenous dynamic IO model with layers of techniques. Metroeconomica 2016;67(4):632–66. http://dx.doi.org/10.1111/meca.12112.

[12] Hartwig J, Kockat J, Schade W, Braungardt S. The macroeconomic effects of ambitious energy efficiency policy in Germany–combining bottom-up energy modelling with a non-equilibrium macroeconomic model. Energy 2017;124:510–20. http://dx.doi.org/10.1016/j.energy.2017.02.077.

[13] Wiebe KS, Bjelle EL, Többen J, Wood R. Implementing exogenous scenarios in a global MRIO model for the estimation of future environmental footprints. J Econ Struct 2018;7(1):1–18. http://dx.doi.org/10.1186/s40008-018-0118-y.

[14] Wilting HC, Faber A, Idenburg AM. Investigating new technologies in a scenario context: description and application of an input–output method. J Clean Prod 2008;16(1):S102–12. http://dx.doi.org/10.1016/j.jclepro.2007.10.017.

[15] Lenzen M. Aggregation versus disaggregation in input–output analysis of the environment. Econ Syst Res 2011;23(1):73–89. http://dx.doi.org/10.1080/09535314.2010.548793.

[16] Duchin F. Structural economics: Measuring change in technology, lifestyles, and the environment. Island Press; 1998.

[17] Vendries Algarin J, Hawkins TR, Marriott J, Scott Matthews H, Khanna V. Disaggregating the power generation sector for input-output life cycle assessment. J Ind Ecol 2015;19(4):666–75. http://dx.doi.org/10.1111/jiec.12207.

[18] Duarte R, Langarita R, Sánchez-Chóliz J. The electricity industry in Spain: A structural analysis using a disaggregated input-output model. Energy 2017;141:2640–51. http://dx.doi.org/10.1016/j.energy.2017.08.088.

[19] Allan G, McGregor P, Swales J, Turner K. Impact of alternative electricity generation technologies on the scottish economy: an illustrative input—output analysis. Proc Inst Mech Eng 2007;221(2):243–54. http://dx.doi.org/10.1243/09576509JPE301.

[20] Wolfram P, Wiedmann T, Diesendorf M. Carbon footprint scenarios for renewable electricity in Australia. J Clean Prod 2016;124:236–45. http://dx.doi.org/10.1016/j.jclepro.2016.02.080.

[21] Wiedmann TO, Suh S, Feng K, Lenzen M, Acquaye A, Scott K, et al. Application of hybrid life cycle approaches to emerging energy technologies–the case of wind power in the UK. Environ Sci Technol 2011;45(13):5900–7. http://dx.doi.org/10.1021/es2007287.

[22] Duchin F, Levine SH. Sectors may use multiple technologies simultaneously: The rectangular choice-of-technology model with binding factor constraints. Econ Syst Res 2011;23(3):281–302. http://dx.doi.org/10.1080/09535314.2011.571238.

[23] Duchin F, Levine SH. The rectangular sector-by-technology model: not every economy produces every product and some products may rely on several technologies simultaneously. J Econ Struct 2012;1(1):1–11. http://dx.doi.org/10.1186/2193-2409-1-3.

[24] Duchin F, Levine SH. Choosing among alternative technologies: conditions for assuring the feasibility of an input–output database or scenario. Econ Syst Res 2017;29(4):541–56. http://dx.doi.org/10.1080/09535314.2017.1301396.

[25] Kätelhön A, Bardow A, Suh S. Stochastic technology choice model for consequential life cycle assessment. Environ Sci Technol 2016;50(23):12575–83. http://dx.doi.org/10.1021/acs.est.6b04270.

[26] Stadler K, Wood R, Bulavskaya T, Södersten C-J, Simas M, Schmidt S, et al. EXIOBASE 3: Developing a time series of detailed environmentally extended multi-regional input-output tables. J Ind Ecol 2018;22(3):502–15. http://dx.doi.org/10.1111/jiec.12715.

[27] Peters JC. The GTAP-power data base: Disaggregating the electricity sector in the GTAP data base. J Glob Econ Anal 2016;1(1):209–50. http://dx.doi.org/10.21642/JGEA.010104AF.

[28] Chepeliev M. GTAP-power data base: Version 10. J Glob Econ Anal 2020;5(2):110–37. http://dx.doi.org/10.21642/JGEA.050203AF.

[29] Eurostat. Energy statistics database. 2022, URL: https://ec.europa.eu/eurostat/web/energy/data/database, [last accessed on 2022/07/20].

[30] Eurostat. ESA supply, use and input-output tables database. 2022, URL: https://ec.europa.eu/eurostat/web/esa-supply-use-input-tables/data/database, [last accessed on 2022/07/20].

[31] Eurostat. NACE Rev. 2 - Statistical classification of economic activities. 2008, URL: https://ec.europa.eu/eurostat/web/products-manuals-and-guidelines/-/ks-ra-07-015, [last accessed on 2022/02/02].

[32] UNSD. International recommendations for energy statistics. 2011, URL: https://unstats.un.org/unsd/energystats/methodology/ires/, [last accessed on 2022/02/09].

[33] Eurostat. Demography, population stock and balance database. 2022, URL: https://ec.europa.eu/eurostat/web/population-demography/demography-population-stock-balance/database, [last accessed on 2022/10/01].

[34] Eurostat. National accounts database. 2022, URL: https://ec.europa.eu/eurostat/web/national-accounts/data/database, [last accessed on 2022/07/20].

[35] OECD. Population projections. 2022, URL: https://stats.oecd.org/Index.aspx?DataSetCode=POPPROJ, [last accessed on 2022/10/01].

[36] OECD. Real GDP long-term forecast (indicator). 2022, http://dx.doi.org/10.1787/d927bc18-en, [last accessed on 2022/10/01].

[37] Wood R. Construction, stability and predictability of an input–output time-series for Australia. Econ Syst Res 2011;23(2):175–211. http://dx.doi.org/10.1080/09535314.2011.564156.

[38] Papke LE, Wooldridge JM. Econometric methods for fractional response variables with an application to 401 (k) plan participation rates. J Appl Econometrics 1996;11(6):619–32. http://dx.doi.org/10.1002/(SICI)1099-1255(199611)11:6<619::AID-JAE418>3.0.CO;2-1.

[39] Ramalho EA, Ramalho JJ, Murteira JM. Alternative estimating and testing empirical strategies for fractional regression models. J Econ Surv 2011;25(1):19–68. http://dx.doi.org/10.1111/j.1467-6419.2009.00602.x.

[40] Barth JR, Lin D, Yost K. Small and medium enterprise financing in transition economies. Atl Econ J 2011;39(1):19–38. http://dx.doi.org/10.1007/s11293-010-9260-0.

[41] Kimmich C, Fischbacher U. Behavioral determinants of supply chain integration and coexistence. J Forest Econ 2016;25:55–77. http://dx.doi.org/10.1016/j.jfe.2016.08.001.

[42] Burke PJ. The national-level energy ladder and its carbon implications. Environ Dev Econ 2013;18(4):484–503. http://dx.doi.org/10.1017/S1355770X13000090.

[43] Koch SF. On the performance of fractional multinomial response models for estimating Engel Curves. Agrekon 2015;54(1):28–52. http://dx.doi.org/10.1080/03031853.2014.974628.

[44] Ramalho EA, Ramalho JJ, Henriques PD. Fractional regression models for second stage DEA efficiency analyses. J Produ Anal 2010;34(3):239–55. http://dx.doi.org/10.1007/s11123-010-0184-0.

[45] Wulff JN. Interpreting results from the multinomial logit model: Demonstrated by foreign market entry. Organizational Res Methods 2015;18(2):300–25. http://dx.doi.org/10.1177/1094428114560024.

[46] StataCorp. Stata statistical software: Release 17. College Station, TX: StataCorp llc.. 2021, URL: https://www.stata.com/.

[47] Buis ML. FMLOGIT: Stata module fitting a fractional multinomial logit model by quasi maximum likelihood. 2008, URL: https://ideas.repec.org/c/boc/bocode/s456976.html, [last accessed on 2021/10/06].

[48] Blazquez J, Fuentes-Bracamontes R, Bollino CA, Nezamuddin N. The renewable energy policy Paradox. Renew Sustain Energy Rev 2018;82:1–5. http://dx.doi.org/10.1016/j.rser.2017.09.002.

[49] R Core Team, R Core Team. R: A language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing; 2021, URL https://www.R-project.org/.

[50] Lahti L, Huovari J, Kainu M, Biecek P. Eurostat R package. 9, (1):2017, p. 385–92, URL https://journal.r-project.org/archive/2017/RJ-2017-019/index.html Version 3.7.5,

[51] Wickham H, Averick M, Bryan J, Chang W, McGowan LD, François R, et al. Welcome to the tidyverse. J Open Source Softw 2019;4(43):1686. http://dx.doi.org/10.21105/joss.01686.