PAPER • OPEN ACCESS

Modelling best fit-curve between China's production and consumption-based temporal carbon emissions and selective socio-economic driving factors

To cite this article: M. Jawad Sajid 2020 IOP Conf. Ser.: Earth Environ. Sci. 431 012061

View the article online for updates and enhancements.

You may also like

- <u>Near-Infrared Photometric Studies of R</u> Canis Majoris Watson P. Varricatt and N. M. Ashok
- <u>The Practical Method for Monitoring</u> <u>Additives in Copper Electroplating Baths</u> <u>Using the Chronopotentiometry Technique</u> Masahiro Kosugi and Toshikazu Okubo
- <u>Consumption-based view on national and</u> regional per capita carbon footprint trajectories and planetary pressuresadjusted human development Sanna Ala-Mantila, Jukka Heinonen, Jack Clarke et al.





DISCOVER how sustainability intersects with electrochemistry & solid state science research



This content was downloaded from IP address 3.144.238.20 on 06/05/2024 at 13:09

Modelling best fit-curve between China's production and consumption-based temporal carbon emissions and selective socio-economic driving factors

M. Jawad Sajid¹

1 School of Management, Xuzhou University of Technology, Xuzhou, Jiangsu province, 221000, China

E-mail: jawad.jaws@outlook.com; 11910@xzit.edu.cn

Abstract. Production and consumption-based approaches are primarily used to determine emissions responsibility at industrial and national levels. China is the world's topmost emitter under both these approaches. Most of the literature especially for China mainly focuses on drivers of direct GHG emissions. This study based on the curvilinear analysis, models best-fit curves between these two emission types and selective driving factors. GDP, GDP/Capita and GNI best-fit curves didn't support EKC hypothesis for production-based emissions, while for consumption-based emissions their curves are in support of EKC. Population, population density, Urbanization, CO₂ intensity and urban population agglomeration all had non-linear best-fit curves. While energy use indicated a linear relation with production-based emissions and non-linear with consumption-based emissions. FDI and renewable energy consumption showed a non-linear negative relation with both emissions. Understanding of the non-linear relationship between vital driving factors and China's emissions under both approaches can help policymakers formulate more informed mitigation policies.

1. Introduction

Reducing GHG emissions is a global objective [1-3], but the increase in worldwide energy-based GHG emissions in 2017 has undermined the global emissions reduction objectives set out in the Paris agreement [4]. About 60% of global GHG emissions are CO₂ emissions [5]. Ever since the 'industrial revolution' CO₂ intensity in 'atmosphere' has greatly increased [6]. The current rate of global GHG emissions can affect the worldwide environment [7]. Carbon emissions from fossil fuel flames are the main cause of global warming [8]. Pursuing many nations to impose mechanisms for the decrease in the consumption of fossil fuels [9]. China is the world top emitter under production and consumptionbased accounting approaches [10]. More than 50% of global outflow trade emissions are from China [11].

Two type of approaches including: consumption-based, where emissions are attributed to the region of final consumption [12-13], and production-based, where emissions are attributed to the region where they are produced irrespective of the fact where they are eventually consumed [14-16]; are extensively employed for calculation of global GHG emissions [17]. PBA, in theory, is similar to IPCC and other international agreements. But the IPCC approach has been strongly criticized because outsourcing mainly takes place between developed and developing nations [18]. This transferring of CO₂ emissions from developed to developing nations is a major problem, developed nation's emissions rise when trade adjustment is considered [19]. Therefore, consumption-based emissions of developed

Content from this work may be used under the terms of the Creative Commons Attribution 3.0 licence. Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI. Published under licence by IOP Publishing Ltd 1

2019 3rd International Conference on Power and Energy Engineering	IOP Publishing
IOP Conf. Series: Earth and Environmental Science 431 (2020) 012061	doi:10.1088/1755-1315/431/1/012061

nations are usually higher than their production-based emissions [20-21]. Regional accounting approach adopted by IPCC encourages direct imports between nations [22-23].

The type of accounting approach adopted deeply influence the allocation of CO₂ emissions responsibility [24]. Hence there is an international debate on approaches and allocation of responsibility for GHG emissions [25-26]. Calculations under PBA are uncomplicated, but it neglects global transport and carbon leakage problems [10]. On the other hand, the consumption-based approach is much fairer when assigning emissions accountability [27-28]. Consumption-based policy is objective and cost-efficient [29]. And it may be needed for sustainable environment [30]. It can help abate worldwide air contamination [31], stimulate ecological comparative advantages and dispersal of technology [32]. The consumption-based approach would pursue importers towards mitigation projects in regions from where they import merchandises [33]. The consumption-based approach also has some disadvantages which may be eliminated by exercising shared responsibility [10; 33-34].

There are three approaches to estimate best-fit curve between dependent (Y) and independent (X) variable: Linear regression, data transformations and curvilinear regression [35]. The curved trend in non-linear relations can be much better explained by non-linear functions for example 'quadratic or cubic' or transformation into a linear function [36]. But transforming data values using some common method of transformation and then performing linear regression may give different results then fitting a curve to un-transformed data, or we can find an equation best fitting our curved data using curvilinear regression [35]. For best fit, we have employed Polynomial, Compound, Growth, Logarithmic, S, Exponential, Inverse, Power and Logistic models.

Most of the current literature on driving factors of China's temporal emissions either focuses on the identification of these factors or their impact on direct emissions while the relationship of these factors with consumption and production based emissions are mostly being ignored. [37] Studied drivers of energy-related CO₂ emissions of 30 provinces of China. Used 'panel data and spatial econometrics models' for their study. [38] Calculated the factors of CO₂ emissions of Chinas business sector. Used VAR and STIRPAT models. [39] Studied the driving factor for China city level carbon emissions. Employed a series of 'dynamic distribution approaches and panel data models.' [40] Also investigated drivers of city level carbon emissions of China. [41] Calculated CO₂ emission decrease potential of Chongqing city of China. Employed LMDI, STIRPAT model' to forecast future carbon emissions.

[42] Researched drivers of energy-related carbon emissions of Beijing. Employed 'Input-output model and SDA to study drivers.' [43] Examined key drivers to predict carbon emissions of Hebei. Employed 'Bivariate correlation analysis, factor analysis, PSO-ELM.' [44] Considered the effect of population-related drivers on carbon emissions in 30 Chinese provinces.

This paper is novel in several aspects first of all non-linear regression analysis has rarely been applied to understand the relationship between different driving factors and carbon emissions of a country. Secondly, in general, there is not much literature available where the relationship between a country's direct (production-based) and carbon footprint (consumption-based) emissions and significant driving factors have been analysed. Finally, to the best of author's knowledge, there is no such attempt has been made to graphically model the relationship between both the direct and consumption-based emissions and important socioeconomic factors of China (which is the largest carbon emitter under both the approaches). In this study, the author has tried to fill this gap. The author estimated best-fit curves for both production and consumption-based emissions with selective key driving factors from 1970 to 2015. A comprehensive presentation of key driving factors temporal relationship with both type of emissions will help policymakers to devise better informed future mitigation policies for both PBA and CBA based emissions of China.

2. Experimental design, materials, and methods

The Data on consumption and production- based emissions of China from 1970 to 2015 was obtained from the Eora database which is based upon [45-46]. The relationship between following socioeconomic factors GDP [47-48], GDP per Capita [49-52], population [49; 51-54], population density [51], urbanization [47-50; 54], FDI [48; 53], energy consumption [55]; Urban agglomeration [56] coupled with consumption & production based yearly emission of China was found out. Plus, the author also included GNI, CO₂ intensity and Renewable energy consumption [57].

2019 3rd International Conference on Power and Energy Engineering **IOP** Publishing IOP Conf. Series: Earth and Environmental Science **431** (2020) 012061 doi:10.1088/1755-1315/431/1/012061

All socio-economic data is from 'The World Bank data bank' [58]. First, the presence of linear or linear-relationship between socio-economic factors (independent variables) and Production and consumption-based emissions (dependent variable) through residual plotting in SPSS was found out. From the graphs, it was apparent that a non-linear relationship exists between most of the socioeconomic factors and PBA & CBA emissions. Bivariate correlation using the Pearson Coefficient is used to establish a relevant relationship between shortlisted variables and carbon emissions [55]. Pearson correlation is a parametric test for a linear relationship between two variable, is not useful for non-linear relation so alternatives should be considered [59].

3. Results

3.1. Model selection

The purpose of regression analysis is to check for influence, significance, and certainty of the factors [60]. The basic linear regression equation is:

$$Y = \alpha + \beta x \tag{1}$$

Where the value of dependent variable is represented by Y, α represents the constant and β represents the value of coefficient of regression and x is independent variable.

For the best fit, the author employed Polynomial, Compound, Growth, Logarithmic, S, Exponential, Inverse, Power and Logistic models to the data; eventually most of the factors best-fit curves in relation with production and consumption-based emissions were obtained through Polynomial model curve fitting. Different powers of x variable are respectively added to the equation to find out their effect on R² till no more noteworthy contributions can be obtained for the value of R², So on until the increase or change in \mathbb{R}^2 is no more significant [35]. Starting by fitting linear regression equation $(y=\alpha+\beta x)$ to the data followed by:

$$Y^2 = \alpha + \beta_1 x + \beta_2 x^2 \tag{2}$$

$$Y^3 = \alpha + \beta_1 x + \beta_2 x^2 + \beta_3 x^3 \tag{3}$$

where Y^2 and Y^3 represent the values of the dependent variable at quadratic and cubic levels respectively.

_

3.1.1. Production-based emissions. Table 1, contains the details about the final selected models based upon the derivation of the highest R^2 values.

Independent variable	Model type	R R2	Adjusted R ²	Std. Error of the Estimate
GDP	Cubic	.950 .903	.901	.666
GDP/Capita	Cubic	.953 .908	.905	.649
Population	Quadratic	.835 .698	.691	1.17
Population density	Quadratic	.835 .698	.691	1.17
Urbanization	Quadratic	.961 .923	.921	.594
FDI	Quadratic	.913 .833	.827	.880
GNI	Cubic	.950 .903	.901	.666
Energy use	Linear	.999 .999	.999	.072
Urban agglomeration	Cubic	.960 .923	.921	.594
CO ₂ Intensity	Quadratic	.810 .656	.647	1.199
Renewable Energy Consumption	Inverse	.994 .989	.988	.226

 Table 1. Summary of selected models (production-based emissions).

The best-fit curves for the independent variables of GDP, GDP/Capita, GNI and Urban agglomerations were obtained under the cubic model. For Population, Population density, Urbanization, FDI and Carbon Intensity, the Quadratic model yielded the highest values of R². For

2019 3rd International Conference on Power and Energy Engineering	IOP Publishing
IOP Conf. Series: Earth and Environmental Science 431 (2020) 012061	doi:10.1088/1755-1315/431/1/012061

both Population and Population density the Cubic model between these two variables and Productionbased emissions of China, could not be tested due to near-collinearity among model terms. Additionally, due to the existence of the non-positive values, the Logarithmic and Power models could not be tested for the independent variable of FDI (Foreign direct investment). Best fit curve for the energy use and production based emissions was obtained under the Linear regression model. And finally for Renewable energy consumption, the best fit curve was obtained under the inverse model. The Cubic model could not be fitted for Renewable energy consumption due to near-collinearity among model terms. ANOVA null hypothesis for both linear and non-linear models was rejected at a significance of .000.

3.1.2. Consumption-based emissions. Table 2, contains the details about the final selected models based upon the derivation of the highest R^2 values.

Independent variable	Model type	R	R ²	Adjusted R ²	Std. Error of the Estimate
GDP	Cubic	.996	.992	.991	.159
GDP/Capita	Cubic	.996	.992	.991	.159
Population	Quadratic	.924	.854	.848	.666
Population density	Quadratic	.924	.854	.848	.666
Urbanization	Cubic	.993	.986	.985	.207
FDI	Cubic	.915	.837	.820	.743
GNI	Cubic	.996	.992	.991	.160
Energy use	Cubic	.999	.998	.997	.081
Urban agglomeration	Cubic	.991	.982	.981	.236
CO ₂ Intensity	Cubic	.928	.861	.854	.617
Renewable Energy Consumption	Power	.991	.982	.981	.066

Table 2. Summary of selected models (consumption-based emissions).

Like production-based emissions, the highest R² values between the independent variables of GDP, GDP/Capita, GNI and Urban agglomerations and the consumption-based emissions were again obtained under the cubic model. Contrary to the best fit curve obtained under the Quadratic and Linear models respectively for the independent variables of carbon intensity, FDI, Urbanization and the energy use with production-based emissions, the best fit curves between these variables and the consumption-based emissions were obtained under the cubic model. For Population and Population density the best-fit curves were obtained under the Quadratic model. Finally, for Renewable energy consumption Power model produced the highest results. ANOVA test for both linear and non-linear regression models was significant at .000.

3.2. Rationalization of best-fit curves

Figure 1a and 1b contains the graphical presentation of the best-fit curves between production and consumption based emissions (dependent variable) and selective socio-economic factors (independent variables) from 1970-2015. GDP, GDP/Capita and GNI regression slopes are steeply concaved approaching last few observations it smoothens. Which means initially slight increases in GDP, GDP/Capita or GNI have seen a larger increase in China's PBA emissions while later on the opposite is true. Approaching end it is steeping again. Thus not supporting EKC hypothesis which advocates the presence of an inverted U-shaped relationship between a country's emissions and its economic progress. The same cannot be said about China's consumption-based emissions relation with GDP, GDP/Capita and GNI. Although their best fit curve is obtained under the cubic model but almost a semi-inverted U shaped regression curve can be observed between these economic factors and consumption-based emissions of China.

IOP Publishing

IOP Conf. Series: Earth and Environmental Science **431** (2020) 012061 doi:10.1088/1755-1315/431/1/012061



Figure 1a. Best-fit curves for Production-based emissions. Where, Y-axis presents PBA (dependent variable) emissions in 'Mt CO₂ per capita'; X-axis presents independent variables: GDP, GDP per capita and GNI (PPP) measured at (current US\$), Population density (people per sq. km of land area), Population in urban agglomerations of more than 1 million, Energy use (Terajoules), Foreign direct

doi:10.1088/1755-1315/431/1/012061

investment, net (BoP, current US\$), Renewable energy consumption (% of total final energy consumption), and urbanization (% of total population).



Figure 1b. Best-fit curves for Consumption- based emissions. Where, Y-axis presents CBA (dependent variable) emissions in 'Mt CO2 per capita'; X-axis presents independent variables: GDP, GDP per capita and GNI (PPP) measured at (current US\$), Population density (people per sq. km of

2019 3rd International Conference on Power and Energy Engineering	IOP Publishing
IOP Conf. Series: Earth and Environmental Science 431 (2020) 012061	doi:10.1088/1755-1315/431/1/012061

land area), Population in urban agglomerations of more than 1 million, Energy use (Terajoules),

Foreign direct investment, net (BoP, current US\$), Renewable energy consumption (% of total final energy consumption), and urbanization (% of total population).

Total population and population density best-fit curves with both production and consumption based emissions have shown hockey stick shaped curves. Which employs that initial increases in China's population and population density didn't seem to be affecting its PBA and CBA emissions much. Afterward slight population increases have (holding other factors constant) resulted in larger increases in PBA and CBA based emissions. Which could be owing to the increased purchasing power of China's general population over time.

Very steeped slightly convexed best fit curves are obtained for production and consumption-based emissions and urbanization. Which means in the beginning increases in China's urbanization rate observed a lower rate of increases in its PBA and CBA emissions. Afterward slight increases in urbanization rate have resulted in large increases in PBA and CBA emissions. The same observation holds for best-fit curves between urban population agglomerations and PBA and CBA based emissions of China.

Energy use best-fit curve with China's production based emissions were obtained with linear model. Which means (holding other factors constant) every unit increase in energy use will result in .004 units increase in PBA emissions. While for consumption-based emissions its best fit curve was obtained at cubic level. Which with slight variations also indicate more or less a linear trend.

CO₂ intensity best-fit curves with both production and consumption-based emissions show hockey stick shaped patterns. While FDI and renewable energy consumption have shown negatively sloped best-fit curves with both production and consumption-based emissions. For FDI these curves are slightly concaved while for renewable energy consumption, these curves are slightly convexed.

4. Conclusion and policy implications

The purpose of this paper was to find out the best-fit curves between production & consumption-based emissions and vital socio-economic factors of the topmost carbon emitter China. Until now most of the literature takes in to account only direct emissions while ignoring these main two accounting approaches for GHG emissions. This paper will not only be helpful specifically to Chinese policymakers but also to other scholars and governments concerned with environmental mitigation. The main points for policy guidance are summarized below:

- 1) GDP, GDP/Capita and GNI best-fit curves with PBA emissions didn't indicate the presence of the EKC hypothesis. While their best-fit curves with CBA supported the presence of the EKC hypothesis and shown somewhat inverted semi U shaped curves. Which indicates that the Chinese government cannot allow unchecked growth based on the EKC theory, i.e., in the hope that after reaching a certain peak its emissions will come down with the further growth of its GDP. Our results indicated no clear presence of the EKC relationship between direct emissions of China and the GDP, GDP/Capita and GNI.
- 2) On the other hand, there is some evidence of the existence of the EKC curve between China's carbon footprint (consumption-based emissions) and these socio-economic factors. Which means with further economic growth (GDP, GDP/Capita and GNI), China's consumption-based emissions are expected to decrease. This indicates that China's rapid economic growth has resulted in decreasing degree of foreign carbon imports as compared to its carbon exports. Due to this reason, China as a nation can benefit from an emission accountability system based upon its carbon footprint (consumption-based) as compared to direct emissions. Consumption-based emissions accounting approach can also help the Chinese government to maintain its rapid economic growth while witnessing a decrease in its carbon footprint (after a certain point). Which as per this study's findings, would not be possible under a production-based approach (direct emissions).
- 3) It is recommended that the Chinese government should pursue the implementation of the consumption-based method under the IPCC and at other international forums. The consumption-based system also will particularly save China from the problem of the global carbon leakage. Not only China's consumption-based emissions are less than its production-based emissions but

also a consumption-based emissions accountability mechanism can help China achieve future economic growth while reducing its carbon footprint.

- 4) Population, population density and CO₂ emission intensity all have shown hockey stick shaped curves with both production and consumption-based emissions. Which means initially with an increase in these factors both the direct and consumption-based emissions did not increase significantly. But after some time a smaller amount of increase in population, population density, and CO₂ emission intensity have witnessed the larger amount of direct and consumption-based emissions. Which means the Chinese government at all costs should control future increases in population, population density, and CO₂ emission intensity, and CO₂ emission intensity, and CO₂ emission intensity.
- 5) Very steeped slightly convexed best fit curves were obtained for production and consumptionbased with Urbanization and urban population agglomerations. It indicates that for mitigation of China's future emissions the rapid phenomenon of urbanization in China should be stopped or slowed as much as possible. The rural population should be discouraged to move to urban cities which is the main cause of conversion of the rural population into urban population in China. Furthermore, to reduce the impact of urban population agglomerations on both the production and consumption-based emissions urban infrastructures should be made more environmentally friendly, residents in the urban agglomerations should be encouraged to improve their consumption habits, etc.
- 6) Energy use has indicated a linear relation with China's production based emissions. Although, it's best fit curve with consumption-based emissions was obtained at cubic level but it was also more or less indicating an almost linear relationship with both the production and consumption-based emissions. Due, to this presence of almost a linear relation (direct relation) improvements in energy use structure and efficiency can help directly in the reduction of the China's consumption and production-based emissions. Chinese government can invest in technological advances to improve its overall energy efficiency.
- 7) Both FDI and penetration of renewable energy showed negatively sloped non-linear curves with production and consumption-based emissions. They might hold the key towards unlocking China's carbon mitigation potential. China has already shifted its attention towards more use of renewable energy to fulfil its energy needs. This process should be further supported and financed. Furthermore, more FDI could be attracted through tax breaks, subsidies and miscellaneous incentives.

5. References

- Q. Cao, W. Kang, M. J. Sajid, and M. Cao, "Measuring China's carbon emissions based on final consumption," Energy Procedia, vol. 152, pp. 853–862, 2018.
- [2] Q. Cao, W. Kang, S. Xu, M. J. Sajid, and M. Cao, "Estimation and decomposition analysis of carbon emissions from the entire production cycle for Chinese household consumption," Journal of Environmental Management, vol. 247, pp. 525–537, Oct. 2019.
- [3] M. Cao, W. Kang, C. Qingren, and M. J. Sajid, "Estimating Chinese rural and urban residents' carbon consumption and its drivers: considering capital formation as a productive input," Environment, Development and Sustainability, pp. 1–22, 2019.
- [4] M. J. Sajid, Q. Cao, and W. Kang, "Transport sector carbon linkages of EU's top seven emitters," Transport Policy, vol. 80, pp. 24–38, May 2019.
- [5] H. Vidyarthi, "An econometric study of energy consumption, carbon emissions and economic growth in South Asia: 1972-2009," World Journal of Science, Technology and Sustainable Development, vol. 11, pp. 182-195, 2014.
- [6] C. Zhou, S. Wang and K. Feng, "Examining the socioeconomic determinants of CO₂ emissions in China: A historical and prospective analysis," Resources, Conservation & Recycling, vol. 130, p. 1–11, 2018.
- [7] M. Jaforullah and A. King, "The econometric consequences of an energy consumption variable in a model of CO₂ emissions," Energy Economics, vol. 63, p. 84–91, 2017.
- [8] S. J. Davis and K. Caldeira, "Consumption-based accounting of CO₂ emissions," PNAS, vol. 12, p. 5687–5692, 2010.

- [9] M. d. P. Pablo-Romero and A. Sánchez-Braza, "The changing of the relationships between carbon footprints and final demand: Panel data evidence for 40 major countries," Energy Economics, vol. 61, p. 8–20, 2017.
- [10] J.-L. Fan, Y.-B. Hou, Q. Wang, C. Wang and Y.-M. Wei, "Exploring the characteristics of production-based and consumption-based carbon emissions of major economies: A multipledimension comparison," Applied Energy, vol. 184, p. 790–799, 2016.
- [11] B. Liddle, "Consumption-based accounting and the trade-carbon emissions nexus," Energy Economics, vol. 69, p. 71–78, 2018.
- [12] T. Wiedmann, "A review of recent multi-region input–output models used for consumptionbased emission and resource accounting," Ecological Economics, vol. 69, pp. 211-222, 2009.
- [13] J. Barrett, G. Peters, T. Wiedman, K. Scott, M. Lenzen, K. Roelich and C. L. Quéré, "Consumption-based GHG emission accounting: a UK case study," Climate Policy, vol. 13, pp. 451- 470, 2013.
- [14] K. Steininger, C. Lininger, S. Droege, D. Roser, L. Tomlinsone and L. Meyerd, "Justice and cost effectiveness of consumption-based versus production-based approaches in the case of unilateral climate policies," Global Environmental Change, vol. 24, pp. 75-87, 2014.
- [15] G. Atkinson, K. Hamilton, G. Ruta and D. V. D. Mensbrugghe, "Trade in 'virtual carbon': Empirical results and implications for policy," Global Environmental Change, vol. 21, pp. 563-574, 2011.
- [16] A. Bows and J. Barrett, "Cumulative emission scenarios using a consumption-based approach: a glimmer of hope?," Carbon Management, vol. 1, pp. 161-175, 2010.
- [17] J. Tian, H. Liao and C. Wang, "Spatial-temporal variations of embodied carbon emission in global trade flows: 41 economies and 35 sectors," Nat Hazards, vol. 78, p. 1125–1144, 2015.
- [18] A. Malik and J. Lan, "The role of outsourcing in driving global carbon emissions," Economic Systems Research, vol. 128, pp. 168-182, 2016.
- [19] K. Kanemoto, D. Moran, M. Lenzen and A. Geschke, "International trade undermines national emission reduction targets: New evidence from air pollution," Global Environmental Change, vol. 24, pp. 52-59, 2014.
- [20] T. Wiedmann, R. Wood, J. C. Minx, M. Lenzen, D. Guan and Rocky Harris, "A CARBON FOOTPRINT TIME SERIES OF THE UK – RESULTS FROM A MULTI-REGION INPUT– OUTPUT MODEL," Economic Systems Research, vol. 22, pp. 19-42, 2010.
- [21] G. P. Peters, J. C. Minx, C. L. Weber and . O. Edenhofe, "Growth in emission transfers via international trade from 1990 to 2008," PNAS, vol. 108, p. 8903–8908, 2011.
- [22] S. J. Davis, G. P. Peters and K. Caldeira, "The supply chain of CO₂ emissions," PNAS, vol. 108, p. 18554–18559, 2011.
- [23] A. Skelton, D. Guan, P. G.P. and D. Crawford-Brown, "Mapping flows of embodied emissions in the global production system," Environmental Science and Technology, vol. 45, pp. 10516-10523, 2011.
- [24] Z. Mi, Y. Zhang, D. Guan, Y. Shan, Z. Liu, R. Cong, X.-C. Yuan and Y.-M. Wei, "Consumption-based emission accounting for Chinese cities," Applied Energy, vol. 184, p. 1073–1081, 2016.
- [25] K. Steen-Olsen, J. Weinzettel, G. Cranston, A. E. Ercin and E. Hertwich, "Carbon, Land, and Water Footprint Accounts for the European Union: Consumption, Production, and Displacements through International Trade," Environmental Science & Technology, vol. 46, p. 10883–10891, 2012.
- [26] D. Caro, F. M. Pulselli, S. Borghesi and S. Bastianoni, "Mapping the international flows of GHG emissions within a more feasible consumption-based framework," Journal of Cleaner Production, vol. 147, pp. 142-151, 2017.
- [27] K. Feng, K. Hubacek, L. Sun and Z. Liu, "Consumption-based CO₂ accounting of China's megacities: The case of Beijing, Tianjin, Shanghai and Chongqing," Ecological Indicators, vol. 47, p. 26–31, 2014.

- [28] J.-L. Fan, Y.-B. Hou, Q. Wang, C. Wang and Y.-M. Wei, "Exploring the characteristics of production-based and consumption-based carbon emissions of major economies: A multipledimension comparison," Applied Energy, p. 790–799, 2016.
- [29] K. Steininger, C. Lininger, S. Droege, D. Roser, L. Tomlinsone and L. Meyerd, "Justice and cost effectiveness of consumption-based versus production-based approaches in the case of unilateral climate policies," Global Environmental Change, vol. 24, pp. 75-87, 2014.
- [30] O. Fernández-Amador, J. F. Francois, D. A. Oberdabernig and P. Tomberger, "Carbon Dioxide Emissions and Economic Growth: An Assessment Based on Production and Consumption Emission Inventories," Ecological Economics, vol. 135, p. 269–279, 2017.
- [31] D. Guan, J. Lin, S. J. Davis, D. Pan, K. He, C. Wang, D. J. Wuebbles, D. G. Streets and Q. Zhang, "Reply to Lopez et al.: Consumption-based accounting helps mitigate global air pollution," PNAS, vol. 111, p. E2631, 2014.
- [32] G. P. Peters and E. G. .. Hertwich, "CO₂ Embodied in International Trade with Implications for Global Climate Policy," Policy analysis, vol. 42, pp. 1401-1407, 2007.
- [33] G. P. Peters, "From production-based to consumption-based national," METHODOLOGICAL AND IDEOLOGICAL OPTIONS, vol. 65, pp. 13-23, 2008.
- [34] M. Lenzen, J. Murray, F. Sack and T. Wiedmann, "Shared producer and consumer responsibility Theory and practice," Ecological Economics, vol. 61, pp. 27-42, 2007.
- [35] J. McDonald, Handbook of Biological Statistics, 3rd ed., Baltimore, Maryland: Sparky House Publishing, 2014.
- [36] Minitab Inc., "Linear, nonlinear, and monotonic relationships," 2010. [Online]. Available: https://support.minitab.com/en-us/minitab/18/help-and-how-to/statistics/basicstatistics/supporting- topics/basics/linear-nonlinear-and-monotonic-relationships/. [Accessed 2018 February 2018].
- [37] Q. Zhang, J. Yang, Z. Sun and F. Wu, "Analyzing the impact factors of energy-related CO₂ emissions in China: What can spatial panel regressions tell us?," Journal of Cleaner Production, vol. 161, pp. 1085-1093, 2017.
- [38] A. Wang and B. Lin, "Assessing CO₂ emissions in China's commercial sector: Determinants and reduction strategies," Journal of Cleaner Production, vol. 164, pp. 1542-1552, 2017.
- [39] S. Wang and X. Liu, "China's city-level energy-related CO₂ emissions: Spatiotemporal patterns and driving forces," Applied Energy, vol. 200, p. 204–214, 2017.
- [40] C. Zhou and S. Wang, "Examining the determinants and the spatial nexus of city-level CO₂ emissions in China: A dynamic spatial panel analysis of China's cities," Journal of Cleaner Production, vol. 171, pp. 917-926, 2018.
- [41] X. Tan, L. Dong, D. Chen, B. Gu and Y. Zeng, "China's regional CO₂ emissions reduction potential: A study of Chongqing city," Applied Energy, vol. 162, p. 1345–1354, 2016.
- [42] J. Wei, K. Huang, S. Yang, Y. Li, T. Hu and Y. Zhang, "Driving forces analysis of energyrelated carbon dioxide (CO₂) emissions in Beijing: an inputeoutput structural decomposition analysis," Journal of Cleaner Production, vol. 163, pp. 58-68, 2017.
- [43] W. Sun, C. Wang and C. Zhang, "Factor analysis and forecasting of CO₂ emissions in Hebei, using extreme learning machine based on particle swarm optimization," Journal of Cleaner Production, vol. 162, pp. 1095-1101, 2017.
- [44] Y. Wang, Y. Kang, J. Wang and L. Xu, "Panel estimation for the impacts of populationrelated factors on CO₂emissions: A regional analysis in China," Ecological Indicators, vol. 78, p. 322–330, 2017.
- [45] K. Kanemoto, D. Moran and E. Hertwitch, "Mapping the Carbon Footprint of Nations," Environmental Science and Technology, p. 10.1021/acs.est.6b03227, 2016.
- [46] K. Kanemoto, D. Moran, M. Lenzen and A. Geschke, "International Trade Undermines National Emissions Targets: New Evidence from Air Pollution," Global Environmental Change, vol. 24, pp. 52- 59, 2014.
- [47] X. Ouyang and B. Lin, "Carbon dioxide (CO₂) emissions during urbanization: A comparative study between China and Japan," Journal of Cleaner Production, vol. 143, pp. 356-368, 2017.

- [48] C. Zhou, S. Wang and K. Feng, "Examining the socioeconomic determinants of CO₂ emissions in China: A historical and prospective analysis," Resources, Conservation & Recycling, vol. 130, pp. 1-11, 2018.
- [49] Q. Zhang, J. Yang, Z. Sun and F. Wu, "Analyzing the impact factors of energy-related CO₂ emissions in China: What can spatial panel regressions tell us?," Journal of Cleaner Production, vol. 161, pp. 1085-1093, 2017.
- [50] A. Wang and B. Lin, "Assessing CO₂ emissions in China's commercial sector: Determinants and reduction strategies," Journal of Cleaner Production, vol. 164, pp. 1542-1552, 2017.
- [51] C. Zhou and S. Wang, "Examining the determinants and the spatial nexus of city-level CO₂ emissions in China: A dynamic spatial panel analysis of China's cities," Journal of Cleaner Production, vol. 171, pp. 917-926, 2018.
- [52] X. Tan, L. Dong, D. Chen, B. Gu and Y. Zeng, "China's regional CO₂ emissions reduction potential: A study of Chongqing city," Applied Energy, vol. 162, p. 1345–1354, 2016.
- [53] S. Wang and X. Liu, "China's city-level energy-related CO₂ emissions: Spatiotemporal patterns and driving forces," Applied Energy, vol. 200, pp. 204-214, 2017.
- [54] Y. Wang, Y. Kang, J. Wang and L. Xu, "Panel estimation for the impacts of populationrelated factors on CO₂ emissions: A regional analysis in China," Ecological Indicators, vol. 78, p. 322–330, 2017.
- [55] W. Sun, C. Wang and C. Zhang, "Factor analysis and forecasting of CO₂ emissions in Hebei, using extreme learning machine based on particle swarm optimization," Journal of Cleaner Production, vol. 162, pp. 1095-1101, 2017.
- [56] X. Xu, H. Huo, J. Liu, Y. Shan, Y. Li, H. Zheng, D. Guan and Z. Ouyang, "Patterns of CO₂ emissions in 18 central Chinese cities from 2000 to 2014," Journal of Cleaner Production, vol. 172, pp. 529-540, 2018.
- [57] R. Roman, J. M. Cansino and J. A. Rodas, "Analysis of the main drivers of CO₂ emissions changes in Colombia (1990-2012) and its political implications," Renewable Energy, vol. 116, pp. 402-411, 2018.
- [58] The World Bank, "The World Bank," 2019. [Online]. Available: databank.worldbank.org. [Accessed 20 January 2019].
- [59] Kent State University Libraries, "SPSS Tutorials: Pearson Correlation," 2018. [Online]. Available: https://libguides.library.kent.edu/SPSS/PearsonCorr. [Accessed 16 February 2019].
- [60] A. Gallo, "Harvard Business review," 2015. [Online]. Available: https://hbr.org/2015/11/arefresher-on-regression analysis. [Accessed 18 February 2019].