Ecological Indicators 61 (2016) 634–645

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

Features and influencing factors of carbon emissions indicators in the perspective of residential consumption: Evidence from Beijing, China

Zhaohua Wang[a,b,c,*], Yuantao Yang[a,b,c]

[a] School of Management and Economics, Beijing Institute of Technology, 100081 Beijing, China
[b] Center for Energy & Environmental Policy Research, Beijing Institute of Technology, 100081 Beijing, China
[c] Collaborative Innovation Center of Electric Vehicles in Beijing, 100081 Beijing, China

ARTICLE INFO

Article history:
Received 15 July 2015
Received in revised form
17 September 2015
Accepted 4 October 2015
Available online 6 November 2015

Keywords:
Residential consumption
Carbon emissions indicators
Input–output analysis
LMDI decomposition

ABSTRACT

This research establishes a residential indirect carbon emissions model through input–output structure decomposition analysis (IO-SDA) and LMDI, analyses the influencing factors affecting urban and rural residential carbon emissions indicators in Beijing through input–output tables from 2000 to 2010, and calculates the direct carbon emissions from residential consumption. As the results suggest, the total carbon emissions from residential consumption in Beijing showed volatility. Growing rural and urban differences in direct emissions, and for indirect emissions, mean that urban greatly exceeds rural in this regard. Rising per capita GDP and population, as well as intermediate demand and sectoral emissions intensity change induce growth in indirect emissions in both urban and rural settings: of which, per capita GDP contributes the most. Declining energy intensity contributes the most to emission reductions, followed by residential consumption rates, the rural to urban consumption ratio and consumption structure effects are much smaller.

1. Introduction

China has become the largest CO_2 emitter in the world (IEA, 2010; Guan et al., 2012), and also one of the countries with the greatest energy consumption (Liu et al., 2009): more than 85% of China's CO_2 emissions come from the combustion of fossil fuel (Guan et al., 2012). The residential energy consumption (REC) in China has grown constantly since 2000, and reached 396.66 Mt standard coal equivalent (SCE) by 2012, with a growth rate of 131.13%: demand is growing faster than in the industrial sectors. Meanwhile, the annual growth rate of carbon emissions caused by residential consumption was 8.7% (Fan et al., 2013), the absolute share of total national emissions reached 10.3% in 2012 (Fan et al., 2015), although far below the world average of 31% (Swan and Ugursal, 2009), it remains the second largest source of emissions in China, second only to industry, and as the proportion of a gradual upward trend, its effects on environment and economy will continue to strengthen. Therefore, it is particularly important to examine the effects of residential consumption on carbon emissions, and provide evidence for energy conservation and emission reduction policies developing from the perspective of consumers.

The concept of carbon emissions from residential consumption comes from the household energy requirement (Zhu et al., 2012). The household energy requirement refers to that energy consumption during day-to-day life, and can be categorised into direct consumption and indirect consumption. Direct consumption is the energy consumption used to meet energy needs in the daily life of residents, while indirect consumption refers to energy consumption indirectly consumed in the different phases of the lifecycle of goods and services, such as in their production, transportation, and marketing (Park and Heo, 2007; Reinders et al., 2003; Yuan et al., 2015). Similarly, the emissions caused by residential consumption include direct emissions and indirect emissions.

The mainstream methods studied for indirect carbon emissions from residential consumption are input–output analysis (IOA) (Das and Paul, 2014; Fan et al., 2012; Kok et al., 2006), and the consumer lifestyle approach (CLA) (Bin and Dowlatabadi, 2005; Feng et al., 2011; Wang and Yang, 2014; Wei et al., 2007), while the method used to estimate direct carbon emissions is relatively simple and will be shown in Section 2. Kok et al. (2006) used three kinds of input–output method to calculate residential energy consumption and associated carbon emissions in the Netherlands, and noted that the use of different data sources and merging levels measured can

* Corresponding author at: School of Management and Economics, Beijing Institute of Technology, Beijing 100081, China. Tel.: +86 10 68918213; fax: +86 10 68912483.
E-mail address: wangzhaohua@bit.edu.cn (Z. Wang).

http://dx.doi.org/10.1016/j.ecolind.2015.10.015
1470-160X/

lead to different results. Wei et al. (2007) used the CLA to analyse the energy requirement and carbon emissions for rural and urban residents in China, and pointed out that about 26% of domestic energy consumption and 30% of CO_2 emissions arose from the lifestyles of the residents and their related economic activities. Feng et al. (2014) focused on the spatial distribution of production activities leading to CO_2 emissions and accounted consumption-based CO_2 in China's four municipalities through multiregional input–output (MRIO) analysis and China's Interregional Input–Output Tables between 30 provinces in 2007, and noted that urban consumption causes large emissions within its territory and impose much more to surrounding provinces, also urban infrastructure and interregional transportation network development drive CO_2 emissions. Structural decomposition analysis (SDA) is usually considered one of the most effective and widely applied analytical tools that has been used in tackling topics related to energy and environment in IO framework (Diakoulaki et al., 2006). Su and Ang (2012b) had reviewed the SDA applied to energy and emissions with methodological developments comprehensively and systematically. Minx et al. (2011) investigated China's carbon emissions from 1992 to 2007 using the environmental input–output model and structural decomposition analysis (EIO-SDA): the results showed that over 70% of carbon emissions growth were from 2002 to 2007 (matching the result computed by Guan et al. (2009)), and mainly came from capital investment (47%) and export (33%), but not residential consumption (16%), or governmental consumption (3%). Peters et al. (2007) simulated the impacts of changes in China's economic structure, urbanisation, and residents' lifestyle on carbon emissions through an input–output structural decomposition model analysis, and found that, in the process of carbon emissions growth, urbanisation and lifestyle change drove infrastructure construction and the ensuing consumption of urban residents exceeded the rate of change in energy efficiency improvements. Zhu et al. (2012) calculated residential consumption indirect carbon emissions in China with China's 1992–2005 comparable price input–output tables and IO-SDA, and the results showed that rising consumption and declining energy intensity are the most important factors in increasing and decreasing the emissions respectively, while the positive effect of intermediate demand, consumption structure, and population size for emissions growth were much smaller. Zhang et al. (2015) analysed the energy consumption and related air pollution situation and its driving forces in Beijing from 1997 to 2010 by input–output structural decomposition methods from bottom-up and top-down approaches, and noted that the effects of population growth on energy consumption and air pollution were the significant. Wang et al. (2013b) analysed the driving forces for the increment in CO_2 emissions in Beijing from both production and final demand perspectives during 1997–2010 based on IO-SDA, and pointed out that production structure change and population growth were two main drivers in emissions growth while emission intensity and per capita final demand volume reduction were the two main offset forces. Tian et al. (2013) quantify the contributions of technology and socio-economic factors to rapid growth of CO_2 emissions in Beijing during 1995–2007 through IO-SDA, and showed that increasing final demand level and production structure change carbonised Beijing significantly, while energy intensity reduction was the sole prominent decarbonizing factor. Xia et al. (2015) simulated urban metabolism processes by input–output model and clarified the underlying reasons behind GHG emissions growth in Beijing by structural decomposition analysis, from the decomposed eight factors, final demand is the main source for the growth of the energy-related emission for most sectors. The general decomposition framework of SDA has been applied in additive decomposition scheme, it also can be developed in multiplicative forms, which has been done by Su and Ang (2014) on attribution analysis based on the generalized Fisher index, and Su and Ang (2015) on decomposing aggregate carbon intensity based on four different combinations of I-O models (Leontief vs. Ghosh model) and imports assumptions (competitive vs. non-competitive imports assumption).

In this research, we used an input–output analysis that could reflect the sources of the inputs to, and the utilisation of the outputs from, production by various sectors of the economy with the additive decomposition, which is the more commonly used form in the SDA literature. By calculating the matrix related to the input–output tables, we reflected the impact of changes in industrial production, and socio-economic factors, on other industries or consumers (Yuan et al., 2015; Zhu et al., 2012), and can fully explain the energy consumption and the emission of pollutants underlying the consumption of products and services. However, as the living standard improved and consumption level ascended, emissions from residential consumption significantly increased and accounted for a growing share in the total emissions, little published literature uses IO-SDA approach to study emissions resulting from residential consumption on a city scale since IO-SDA approach requires time-series input–output tables and sectoral energy data, which are always unavailable for cities, so that provides space for our research.

Beijing, as the capital of China and her second largest city, represents rapid urbanisation, economic growth, and scientific and technological progress. Studies of the characteristics and features of carbon emissions from residential consumption in Beijing, and analysis of influencing factors of carbon emissions indicators in Beijing, is possible with some representativeness for some metropolises in China or around the world, and could direct policy decisions on industrial restricting and GHG mitigation (Wang et al., 2013b). Also it can help to enhance the pertinence and operability of energy conservation and emission reduction policies while developing a better guide for residents as to low carbon consumption and sustainable consumption, and as a reference for other regions or provinces, especially in some large cities where drive the regional economy development in China, drive China towards becoming a low-carbon economy as fast as possible.

There is a technique problem with the simple IO-SDA model: the non-uniqueness of the decomposition results (Guan et al., 2008; Liang et al., 2013; Peters et al., 2007; Rørmose and Olsen, 2005; Wang et al., 2013b), if the number of decomposed factors is n, the number of possible decomposition forms is $n!$ (Dietzenbacher and Los, 1998). Dietzenbacher and Los proposed using the average of all $n!$ decomposition forms to reach the results. But when the number of decomposed factors is large, this method will increase the computational complexity and workload (this method is referred to as D&L in short). Some "shortcut" techniques like polar decomposition, midpoint weighted decomposition, or the weighted average decomposition method have been used to calculate the impacts of variations in decomposed factors on the dependent variables. These approaches reduce the computational complexity at the cost of result accuracy: all the interactive items cannot be completely decomposed, and the obtained results are approximate (Su and Ang, 2012b; Wang et al., 2012). The Logarithmic Mean Divisia Index (LMDI) approach is a complete, and no-residual, decomposition method, and could well overcome the problem of interactive items (Ang et al., 1998), and this approach has also been accorded a wide range of application (Liu et al., 2007; Nie and Kemp, 2014; Wang et al., 2011; Xu et al., 2012, 2014; Zha et al., 2010; Zhao et al., 2010). As reviewed in Su and Ang (2012b), the decomposed methods used in SDA in literatures can be divided into four categories, i.e. ad hoc, D&L (full D&L or an approximate technique), LMDI and Others (including the mean rate of change of MRCI and the parametric Divisia methods), while D&L and LMDI are recommended in empirical studies. The application of LMDI in SDA has been confined to the one-stage model (treat changes in the Leontief matrix as a