



## ANALYSIS

# Structural decomposition analysis of sources of decarbonizing economic development in China; 1992–2006

Youguo Zhang\*

*Institute of Quantitative & Technical Economics, Chinese Academy of Social Sciences, No. 5, Jianguomennei Street, Beijing, 100732, China*

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## ABSTRACT

To analyze and understand decarbonizing economic development in China, this paper undertakes a structural decomposition analysis of the historical change in energy-related carbon intensity in China between 1992 and 2006. The results show that the energy-related carbon intensity in China decreased by about three-fourths between 1992 and 2006 and reduced carbon emissions by about two billion tons. The decline in the energy-related carbon intensity was mainly caused by changes in production pattern, especially changes in energy intensity within each sector between 1992 and 2002. However, the most important driving force of carbon intensity from 2002–2006 was not the energy intensity within each sector but the input mix. On the other hand, changes in demand pattern pushed up the carbon intensity. To further decarbonize the economy in the future, it is important for China to further enforce policies on shaping the production pattern, such as reducing energy intensity, and pay more attention to increasing the sustainability of the demand pattern at the same time.

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## 1. Introduction

Climate change is not only an environmental issue, but also an issue closely related to economic development. The Report to the Seventeenth National Congress of the Communist Party of China (RSCNCCP) of Oct. 15, 2007 wrote that enhancing China's capacity to respond to climate change and contribute to protecting the global climate is now essential to promoting the sound and rapid development of the national economy. How has China contributed to protecting the global climate, by how much, and how can China continue to make such contributions? To partly answer the above questions, it is useful to undertake a decomposition analysis of the historical change in energy-related carbon intensity in China since energy-related CO<sub>2</sub> is the most important man-made greenhouse gas in China (Zhou et al., 2003).

An increasing number of studies on energy-related carbon intensity decomposition have been reported in recent years; most of these studies have been conducted in developed rather than developing countries. However, it is more important to analyze the carbon intensity change in developing countries because this would aid in optimizing the fuel mix and economic structure (Fan et al., 2007). Among these studies, Fan et al. (2007) focused on the energy-related carbon intensity of China. The authors quantified two driving forces of primary energy-related carbon intensity and four driving forces of the material production sectors' energy-related carbon intensity from 1980–2003. Four kinds of fuel (coal, petroleum products, natural gas and electricity) and three aggregated industries (primary industry, secondary industry and

tertiary industry) were included in their analysis. Their results show that more than 99% of the decline in primary energy-related carbon intensity was attributable to real energy intensity declines. However, they argued that policies to improve the decline of carbon intensity should focus not only on the decline in energy intensity but also on the change in the primary energy mix.

However, the decomposition technique used in Fan et al. (2007) and most of the other studies on energy-related carbon intensity decomposition is index decomposition analysis (IDA).<sup>1</sup> Another popular decomposition technique, structural decomposition analysis (SDA), is rarely adopted in the literature on carbon intensity decomposition. The simple reason may be that SDA uses information from input–output tables, while IDA uses only aggregate data at the sector-level, which is the main difference between the two techniques (Hoekstra and van den Bergh, 2003). The simplicity and flexibility of IDA thus makes it easily adoptable compared to SDA, for which input–output tables are needed (Ang, 2004). However, a lower data requirement is clearly also a disadvantage since IDA is capable of less detailed decompositions of the economic structure than SDA. SDA can distinguish between a range of technological effects and final demand effects that are not possible in the IDA framework (Hoekstra and van den Bergh, 2003).

Another important advantage of SDA is that the input–output model includes indirect and induced effects in the analysis (Rose and

<sup>1</sup> IDA is also sometimes referred to as 'index number analysis' or 'energy decomposition'. SDA is sometimes referred to as 'input–output structural decomposition analysis' or 'input–output decomposition analysis' (Hoekstra and van den Bergh, 2003).

\* Tel.: +86 10 85195713; fax: +8610 65125895.

E-mail address: [zhyouguo@cass.org.cn](mailto:zhyouguo@cass.org.cn).

Casler, 1996; Hoekstra and van den Bergh, 2003). With regard to the decomposition analysis of carbon intensity, applying input–output techniques allows us to trace the direct and indirect CO<sub>2</sub> emissions associated with a product and to assess the carbon embodied in a product (Machado et al., 2001). Indirect environmental effects are not caused directly by the agent, but are consequences of producing the inputs needed by the agent in order to produce a final product (Mongelli et al., 2006). Therefore, in discussing carbon emissions caused by end-user demand, both direct and indirect carbon emissions must be considered. However, other approaches do not allow us to look so deeply into the internal productive linkages within an economy with implications on CO<sub>2</sub> emissions (Taracón Morán and del Río González, 2007). Therefore, a SDA based on an input–output table is particularly suitable to account for the indirect effects on one industry of the structural and productivity changes that take place in other industries and are transmitted by these industries through supplied intermediate inputs (Milana, 2001). Several publications have applied SDA to classifying carbon emissions, such as Wier (1998), Munksgaard et al. (2000), Seibel (2003), and Rørmose and Olsen (2005), while few studies report using SDA to classify carbon intensity specifically.

In addition, the value of the total energy consumption elasticity of China was larger than one between 2003 and 2005, which stands in sharp contrast to the value between 1980 and 2002 (NBS, 1985–2007). This may lead to a different trend of carbon intensity in recent years. Therefore, using SDA with information from more disaggregated sectors to study the effects of every driving force on energy-related carbon intensity in China between 1992 and 2006 would be particularly worthwhile. The rest of the sections of this paper are arranged as follows.

## 2. Method and data preparation

In this paper, six driving forces determining the change in carbon intensity have been identified, namely the final demand allocation structure, final demand product structure, input mix, energy intensity, fuel mix, and carbon factor. The final demand allocation structure is defined as the shares of domestic final demand categories (household consumption, public consumption, fixed capital formation and export) in the total domestic final demand. The final demand product structure is the share of every kind of product or service in the domestic final demand categories. The input mix is the share of every kind of product or service in the total domestic intermediate input requirements of each sector. The energy intensity is the ratio of the total energy consumption and total output of each sector. The fuel mix is the share of every kind of fuel in the total energy consumption of each sector. Finally, the carbon factor is the amount of carbon emissions consumed per unit of each kind of fuel.

Among the six driving forces, the input mix, energy intensity, fuel mix, and carbon factor<sup>2</sup> are determined by the behaviors of firms. We thus define this set of variables to be the production pattern. On the other hand, the final demand allocation structure and final demand product structure can be regarded as the demand pattern. The combination of production pattern and demand pattern defines the economic development mode.

### 2.1. Input–output model for calculating energy-related carbon intensity

We use an environmental–economic input–output model to calculate energy-related carbon intensity. We assume that the intermediate input coefficient matrix  $A$  between production sectors can be separated into  $A^d$  and  $A^{im}$ , representing the intermediate input

<sup>2</sup> The carbon emissions factors of electricity and heat are decided by the firms supplying electricity and heat, while the carbon emissions factors of primary fuels are kept constant.

requirements of domestic goods and import goods, with emissions proportional to output. Let  $Q$  denote the total carbon emissions from all the production sectors; then according to the basic principle of the input–output model, we obtain the following function:

$$Q = Q(C, F, E, L, M, S, y^d) = CFELMSy^d \quad (1)$$

where  $C$  is a  $1 \times 19$  vector whose element  $c_k$  represents the carbon emissions factor of fuel  $k$ ;  $F$  is a  $19 \times 26$  matrix, whose element  $f_{rj}$  represents the ratio of the amount of fuel  $r$  consumed by sector  $j$  to the total amount of fuel consumed by sector  $j$ ;  $E$  is a  $26 \times 26$  diagonal matrix, whose diagonal element  $e_{ii}$  represents the energy intensity of sector  $i$ ;  $L = (I - A^d)^{-1}$  is the Leontief inverted matrix, which reflects the relationship between the final demand vector and the total output vector;  $M$  is the  $26 \times 4$  final used domestic product structure matrix, whose element  $m_{kj}$  represents the share of the final used domestic product from sector  $j$  in the final demand of domestic products category  $k$ ;  $S$  is a  $4 \times 4$  diagonal final demand allocation matrix of domestic products, whose diagonal element  $s_k$  represents the ratio of the final demand of domestic products category  $k$  (such as household consumption) to the total final demand of domestic products, and  $y^d$  is a scalar representing the total final demand for domestic products.

Let  $q = Q/y^d$ , then  $q$  can be regarded as the carbon intensity of the total final demand of domestic products, namely the carbon emissions per unit of final domestic product demand. We call  $q$  the comprehensive carbon intensity. From Eq. (1), it is clear that

$$q = q(C, F, E, L, M, S) = CFELMS \quad (2)$$

Eq. (2) reflects the determinants of carbon intensity. If we further set  $W = CFEL$  and  $H = CFELM$ , then  $W$  is the  $1 \times 26$  carbon intensity vector of the final used products, and  $H$  is the  $1 \times 4$  carbon intensity vector of the final demand categories.

### 2.2. Structural decomposition

Let the total carbon emissions and the comprehensive carbon intensity in period  $t$  be  $Q_t$  and  $q_t$ , respectively; then the changes between two points in time, i.e.  $\Delta Q = Q_t - Q_{t-1}$  and  $\Delta q = q_t - q_{t-1}$ , can be decomposed as follows:

$$\Delta Q = Q(\Delta C) + Q(\Delta F) + Q(\Delta E) + Q(\Delta L) + Q(\Delta M) + Q(\Delta S) + Q(\Delta y^d) \quad (3)$$

$$\Delta q = q(\Delta C) + q(\Delta F) + q(\Delta E) + q(\Delta L) + q(\Delta M) + q(\Delta S). \quad (4)$$

Using Eqs. (3) and (4), we can calculate the effects of each determinant on both the total carbon emissions and the comprehensive carbon intensity, but the forms of Eqs. (3) and (4) are not unique (Dietzenbacher and Los, 1998).

The most common way to compute the form of the structural decomposition, such as in Eqs. (3) and (4) is to let the value of one determinant vary while holding all the others constant at time point  $t-1$  (Laspeyres index) or at the time point  $t$  (Paasche index). However, this method has the theoretical shortcoming of decomposition residuals, because there are always large differences between the values of the determinants at time point  $t-1$  and the time point  $t$ . To address this problem, two popular methods have appeared in empirical studies in recent years: one is the so-called two polar decomposition recommended by Fujimigari (1989) and Betts (1989), which has been used in many studies such as Munksgaard et al. (2000), while another is the so called midpoint weight decomposition, which has also been used widely such as Wolff (1994).

However, as shown by Dietzenbacher and Los (1998), the latter two methods also suffered from theoretical shortcomings, in that if a given

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