Exploring Change in China's Carbon Intensity: A Decomposition Approach

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Abstract: This paper aims to explore the change of CO_2 intensity in China at both national and provincial levels. To serve this purpose, we introduce a decomposition model which integrates the merits of index decomposition analysis and production-theoretical decomposition analysis. Based on the decomposition, we also estimate the potential reduction of CO_2 intensity for China and its provinces. Using a panel data set including China's 30 provinces during the period of 2006–2012, the empirical analysis is conducted and meaningful results are obtained. First, the potential energy intensity change was the dominant driving factor for the decrease of CO_2 intensity, which contributed to a total reduction of 19.8%. Second, the energy efficiency change and the CO_2 emission factor change also play positive roles in the CO_2 intensity reduction for most provinces. Third, provinces in the western area generally showed a relatively large potential reduction in CO_2 intensity, while those in the eastern area only demonstrated a small reduction.

Keywords: index decomposition analysis; production-theoretical decomposition analysis; China; carbon intensity

1. Introduction

Global warming has increasingly attracted attention worldwide and has become a serious challenge for human society. As the major component of greenhouse gas, the increase in CO_2 emissions is of particular concern. According to the International Energy Agency (IEA), the global CO_2 emissions reached 31.7 Gt CO_2 in 2012, and China is the largest contributor, accounting for 26% of the world's total emissions. Consequently, global CO_2 emission mitigation requires a commitment from China to control and reduce emissions from all sources, especially that from fossil fuels. If this does not occur, global CO_2 emissions are expected to increase at an even faster rate, due to the contribution of China. Therefore, understanding the features of China's CO_2 emissions is of vital importance. There is a large body of studies analyzing the factors which are influencing China's CO_2 emission. See, for example [1–6].

Unlike developed countries, China creates its emissions reduction target using CO_2 intensity (defined as CO_2 emissions per GDP) as an important indicator. For instance, in 2009, China made a commitment to reduce its CO_2 intensity by 40%–45% from 2005 to 2020. In the "Twelfth Five-Year Plan" (2011–2015), the CO_2 intensity is scheduled to be reduced by 17%, compared to the 2010 level. An increasing number of studies are placing an emphasis on investigating the driving force of change in China's CO_2 intensity. Representative studies include [7–11].

China is a large country with enormous provincial variations in resource endowments and economic development. Accordingly, there are also large provincial diversities in the change of CO_2 intensity. Therefore, China's emissions reduction targets are usually decomposed at a regional level and assigned to each of its provinces. Thus, a lack of accountability for reduction efforts at the provincial level may lead to a poor implementation of national policy [12]. As a result, tracking the change in China's CO_2 intensity at both a national and provincial level is particularly important for policy makers. However, as far as we know, very few studies have paid attention to the variations of CO_2 intensity change across China's provinces. For example, Zhang et al. [13] employed the LMDI method to explore the driving factors of carbon intensity in China's 29 Chinese provinces, from 1995 to 2012. Furthermore, Xu et al. [14] analyzed the regional contributions to the national carbon intensity in China in different Five-Year Plan periods. The purpose of this paper is to explore the driving forces of China's CO_2 intensity change at the provincial level, as well as at the national level, using a newly developed decomposition method. Specifically, we decompose the carbon intensity change into six predefined components for each province, respectively. For the purpose of empirical study, we analyze the carbon intensity change for China's 30 provinces between 2006 and 2012. This can help us gain a deeper understanding of the carbon intensity change at China's provincial level, through exploring the different driving forces. Similarly, we attribute the change in the carbon intensity of China as a whole into seven predefined effects. We empirically investigate China's carbon intensity change on a year-by-year basis. In summary, for the analysis of the nation, we explore the time-serial features. However, for the provinces, we focus on the cross-sectional features.

Technically, the driving factors of CO_2 intensity change can be analyzed by attributing them to several pre-defined effects, using decomposition analysis. In this context, index decomposition analysis (IDA) has become a popular analytical tool. Xu and Ang [15] provided a comprehensive literature review on applying IDA to CO_2 emission studies. Ang [16] compared various IDA methods and concluded that the Logarithmic Mean Divisia Index (LMDI) method was preferable, as it possesses all of the three desirable properties: factor-reversal, time-reversal, and zero-value robust [17]. Currently, the LMDI method is widely used in energy and environmental studies. Despite its strengths, some fundamental factors, such as technical efficiency change and technological change, which play critical roles in CO_2 intensity change, cannot be taken into account by the existing IDA framework.

Recently, some studies (e.g., [18–22]) have proposed another decomposition framework, based on the production theory which is termed PDA by [22]. PDA enables us to analyze the impact of production technology on CO_2 intensity change, thereby providing a useful complementary approach to IDA. However, as pointed out in [23], there are some inconsistencies when applying PDA to quantify the effects of industrial structure change and energy composition change. Regarding this issue, some studies advocate the combination of IDA and PDA. For example, Kim and Kim [24] proposed a decomposition model combining IDA and PDA for investigating industrial CO_2 emission trends (Although Kim and Kim [24] termed the decomposition model as "production-based decomposition", it actually uses PDA to quantify the impacts from production theory at the sectorial level, and employs IDA for summing up these effects at the national level, directly quantifying the effects of industrial change and energy composition change). Lin and Du [23] developed another approach combining IDA and PDA to explore the mechanism of energy intensity change.

This paper proposes a modification of Kim and Kim [24], based on the global Malmquist productivity index, to explore the change in China's carbon intensity. The introduction of global benchmark technology avoids the calculation of cross-period distance functions, so that the issue of infeasibility can be effectively precluded [25,26].

The remainder of this paper is structured as follows. Section 2 describes the methodology in further detail. Section 3 presents the empirical results and discussion. Section 4 concludes the paper.

2. Methodology

2.1. Shephard Energy Distance Function

Following [24], this paper establishes the decomposition model based on the Shephard energy distance function. We consider a production process where energy (E) is used to produce value-added as the desirable output (Y) and CO_2 emissions as the undesirable output (C) (In literature, labor and capital are also widely modeled as inputs. In this paper, we do not include them for the following considerations. On the one hand, data on labor and capital in industrial subsectors in provinces in China are unavailable. On the other hand, we can focus on the link between CO_2 emissions and energy productivity. Note, this is also a common practice in [22,24]). As different industrial sub-sectors use different types of production technology, we construct a production frontier for each sub-sector, respectively. The production technology for the industrial sub-sector $i = 1, \ldots, I$ at time period $t = 1, \ldots, T$, can be expressed as:

$$T_{i,t}^c = \{(E_{i,t}, Y_{i,t}, C_{i,t}) : E_{i,t} \text{ can produce}(Y_{i,t}, C_{i,t})\} \tag{1}$$

The above definition describes the production possibility set for the industrial sub-sector i within each time period t. Thus, it is regarded as the contemporaneous benchmark technology. Following [25,26], we further define the global benchmark technology for the industrial sub-sector i as:

$$T_i^g = \left\{ T_{i,1}^c \cup T_{i,2}^c \cup \ldots \cup T_{i,T}^c \right\} \tag{2}$$

According to [22], the Shephard energy distance function, relative to the contemporaneous benchmark technology and the global benchmark technology, can be described as Equations (3) and (4), respectively.

$$D_{i,t}^c(E_{i,t}, Y_{i,t}, C_{i,t}) = \sup\left\{ \theta : (E_{i,t}/\theta, Y_{i,t}, C_{i,t}) \in T_{i,t}^c \right\} \tag{3}$$

$$D_i^g(E_{i,t}, Y_{i,t}, C_{i,t}) = \sup\left\{ \theta : (E_{i,t}/\theta, Y_{i,t}, C_{i,t}) \in T_i^g \right\} \tag{4}$$

Using a DEA-type linear programming technique, the Shephard energy distance function can be estimated through the following optimization problems:

$$
\begin{aligned}
\left[D_{i,t}^c(E_{i,t}, Y_{i,t}, C_{i,t}) \right]^{-1} &= \min \theta \\
s.t. \quad & \sum_{n=1}^{N} \lambda_n E_{i,t}^n \leq \theta E_{i,t} \\
& \sum_{n=1}^{N} \lambda_n Y_{i,t}^n \geq Y_{i,t} \\
& \sum_{n=1}^{N} \lambda_n C_{i,t}^n = C_{i,t} \\
& \lambda_n \geq 0, n = 1, \ldots, N
\end{aligned} \tag{5}
$$

$$
\begin{aligned}
\left[D_i^g(E_{i,t}, Y_{i,t}, C_{i,t}) \right]^{-1} &= \min \theta \\
s.t. \quad & \sum_{t=1}^{T} \sum_{n=1}^{N} \lambda_{n,t} E_{i,t}^n \leq \theta E_{i,t} \\
& \sum_{t=1}^{T} \sum_{n=1}^{N} \lambda_{n,t} Y_{i,t}^n \geq Y_{i,t} \\
& \sum_{t=1}^{T} \sum_{n=1}^{N} \lambda_{n,t} C_{i,t}^n = C_{i,t} \\
& \lambda_{n,t} \geq 0, n = 1, \ldots, N, t = 1, \ldots, T
\end{aligned} \tag{6}
$$

The global technology establishes a single benchmark for all of the observations in the sample. The change of $D_i^g(E_{i,t}, Y_{i,t}, C_{i,t})$ provides a measure of the energy productivity change. A global Malmquist energy productivity index (MEPI) is defined as:

$$MEPI_{i,(t,\tau)}^n = \frac{D_i^g\left(E_{i,t}^n, Y_{i,t}^n, C_{i,t}^n\right)}{D_i^g\left(E_{i,\tau}^n, Y_{i,\tau}^n, C_{i,\tau}^n\right)} \tag{7}$$

It is worth pointing out that, compared with the conventional Malmquist productivity index (The term "conventional" refers to the Malmquist productivity index that is built on the contemporaneous benchmark technology. In the context of energy efficiency, Wang et al. [27] and Wu et al. [28] proposed two different types of Malmquist energy productivity indexes, based on the contemporaneous benchmark technology), the global Malmquist productivity index is circular and immune to the infeasibility problem([25,26]).

MEPI can be decomposed as:

$$
\begin{aligned}
MEPI_{i(t,\tau)}^n &= \frac{D_{i\tau}^c\left(E_{i\tau}^n, Y_{i\tau}^n, C_{i\tau}^n\right) / D_i^g\left(E_{i\tau}^n, Y_{i\tau}^n, C_{i\tau}^n\right)}{D_{it}^c\left(E_{it}^n, Y_{it}^n, C_{it}^n\right) / D_i^g\left(E_{it}^n, Y_{it}^n, C_{it}^n\right)} \times \frac{1/D_{i\tau}^c\left(E_{i\tau}^n, Y_{i\tau}^n, C_{i\tau}^n\right)}{1/D_{it}^c\left(E_{it}^n, Y_{it}^n, C_{it}^n\right)} \\
&= \frac{BPG_i^n(\tau)}{BPG_i^n(t)} \times EC_{i(t,\tau)}^n \\
&= BPC_{i(t,\tau)}^n \times EC_{i(t,\tau)}^n
\end{aligned}
\tag{8}
$$

$BPG_i^n \leq 1$ is a best practice gap between the global technology (T_i^g) and the contemporaneous technology ($T_{i,t}^c$), measured along the energy direction. $BPC_{i,(t,\tau)}^n$ is the change of BPG_i^n. $BPC_{i(t,\tau)}^n > (<) 1$, indicates that the contemporaneous technology is moving closer to (further away from) the global benchmark technology. Thus, $BPC_{i(t,\tau)}^n$ provides a measure of technological change in terms of energy use. $1/D_{it}^c\left(E_{it}^n, Y_{it}^n, C_{it}^n\right)$ is the ratio of the minimum energy input (under the contemporaneous technology) to the real energy input, which is usually defined as the energy use efficiency (denoted as EUE). Thus, $EC_{i(t,\tau)}^n$ is the change in energy use efficiency.

2.2. Decomposition Model

The CO_2 intensity (denoted as *CI*) of region $n = 1, \ldots, N$ can be expressed as:

$$CI_t^n = \sum_{ij} \frac{C_{ij,t}^n}{E_{ij,t}^n} \frac{E_{ij,t}^n}{E_{i,t}^n} \frac{E_{i,t}^n / Y_{i,t}^n}{D_i^g(E_{i,t}^n, Y_{i,t}^n, C_{i,t}^n)} \frac{Y_{i,t}^n}{Y_t^n} \frac{D_i^g(E_{i,t}^n, Y_{i,t}^n, C_{i,t}^n)}{D_{i,t}^c(E_{i,t}^n, Y_{i,t}^n, C_{i,t}^n)} D_{i,t}^c(E_{i,t}^n, Y_{i,t}^n, C_{i,t}^n) \tag{9}$$

where $E_{ij,t}^n$ denotes the consumption of the type-*j* energy in the sub-sector *i* of region *n* at the period *t*, and $C_{ij,t}^n$ represents the CO_2 emissions from $E_{ij,t}^n$. The above expression is a modification of [24]. Unlike [24], we introduce the global benchmark technology to establish the relationship between CO_2 emissions and energy use technology. Our formulation avoids the introduction of the cross-period distance functions, thus avoiding the infeasibility issue.

Using the LMDI method, the change in CO_2 intensity between time period *t* and time period τ can be decomposed as:

$$CI_\tau^n / CI_t^n = D_{EMF} \times D_{EMX} \times D_{PEI} \times D_{STR} \times D_{BPC} \times D_{EC} \tag{10}$$

where $D_{EMF} = \exp\left\{ \sum_{ij} \frac{L(CI_{ij\tau}^n, CI_{ijt}^n)}{L(CI_\tau^n, CI_t^n)} \ln \frac{CI_{ij\tau}^n / E_{ij\tau}^n}{CI_{ijt}^n / E_{ijt}^n} \right\}$;

$$D_{EMX} = \exp\left\{ \sum_{ij} \frac{L(CI_{ij\tau}^n, CI_{ijt}^n)}{L(CI_\tau^n, CI_t^n)} \ln \frac{E_{ij\tau}^n / E_{i\tau}^n}{E_{ijt}^n / E_{it}^n} \right\};$$

$$D_{PEI} = \exp\left\{\sum_{ij} \frac{L(CI_{ij\tau}^n, CI_{ijt}^n)}{L(CI_\tau^n, CI_t^n)} \ln \frac{[E_{i\tau}^n / D_{i\tau}^c(E_{i\tau}^n, Y_{i\tau}^n, C_{i\tau}^n)]/Y_{i\tau}^n}{[E_{it}^n / D_{it}^c(E_{it}^n, Y_{it}^n, C_{it}^n)]/Y_{it}^n}\right\};$$

$$D_{STR} = \exp\left\{\sum_{ij} \frac{L(CI_{ij\tau}^n, CI_{ijt}^n)}{L(CI_\tau^n, CI_t^n)} \ln \frac{Y_{i\tau}^n / Y_\tau^n}{Y_{it}^n / Y_t^n}\right\};$$

$$
\begin{aligned}
D_{BPC} &= \exp\left\{\sum_{ij} \frac{L(CI_{ij\tau}^n, CI_{ijt}^n)}{L(CI_\tau^n, CI_t^n)} \ln \left[\frac{BPG_{i\tau}^n}{BPG_{it}^n}\right]^{-1}\right\} \\
&= \exp\left\{\sum_{ij} \frac{L(CI_{ij\tau}^n, CI_{ijt}^n)}{L(CI_\tau^n, CI_t^n)} \ln \left[BPC_{i(t,\tau)}^n\right]^{-1}\right\}
\end{aligned}
;$$

$$
\begin{aligned}
D_{EC} &= \exp\left\{\sum_{ij} \frac{L(CI_{ij\tau}^n, CI_{ijt}^n)}{L(CI_\tau^n, CI_t^n)} \ln \frac{D_{i\tau}^c(E_{i\tau}^n, Y_{i\tau}^n, C_{i\tau}^n)}{D_{it}^c(E_{it}^n, Y_{it}^n, C_{it}^n)}\right\} \\
&= \exp\left\{\sum_{ij} \frac{L(CI_{ij\tau}^n, CI_{ijt}^n)}{L(CI_\tau^n, CI_t^n)} \ln \left[EC_{i(t,\tau)}^n\right]^{-1}\right\}
\end{aligned}
.$$

$CI_{ij,t}^n = C_{ij,t}^n / Y_t^n$; $L(\cdot, \cdot)$ is a weighting scheme called the logarithmic mean weight, which is expressed as follows:

$$L(x, y) = \begin{cases} (x - y)/(\ln x - \ln y), & x \neq y \\ x, & x = y \end{cases} \tag{11}$$

Equation (10) shows that a change in CO_2 intensity in a region over times, can be decomposed into six components. The first component D_{EMF} is the CO_2 emission factor effect.

The second component D_{EMX} refers to the effect of energy mix change. The third component D_{PEI} captures the energy intensity change under the scenario without energy inefficiency, relative to the global technology. Following [22,24], we refer to this component as the potential energy intensity change. The fourth component D_{STR} is the industrial structure effect, accounting for the impact from the output composition change. The fifth component D_{BPC} is the weighting sum of the reciprocal of $BPC_{i,(t,\tau)}^n$. Thus, it describes the impact from technological change on energy use. The last component D_{EC} is the weighting sum of the reciprocal of $EC_{i,(t,\tau)}^n$, thereby indicating the effect of energy efficiency change.

Analogs to the foregoing derivations, illustrating the change in the overall CO_2 intensity of the whole economy, can be decomposed as:

$$CI_\tau / CI_t = D_{EMF} \times D_{EMX} \times D_{PEI} \times D_{STR} \times D_{ROS} \times D_{BPC} \times D_{EC} \tag{12}$$

where $D_{EMF} = \exp\left\{\sum_{nij} \frac{L(CI_{ij\tau}^n, CI_{ijt}^n)}{L(CI_\tau, CI_t)} \ln \frac{CI_{ij\tau}^n / E_{ij\tau}^n}{CI_{ijt}^n / E_{ijt}^n}\right\};$

$$D_{EMX} = \exp\left\{\sum_{nij} \frac{L(CI_{ij\tau}^n, CI_{ijt}^n)}{L(CI_\tau, CI_t)} \ln \frac{E_{ij\tau}^n / E_{i\tau}^n}{E_{ijt}^n / E_{it}^n}\right\};$$

$$D_{PEI} = \exp\left\{\sum_{nij} \frac{L(CI_{ij\tau}^n, CI_{ijt}^n)}{L(CI_\tau, CI_t)} \ln \frac{[E_{i\tau}^n / D_{i\tau}^c(E_{i\tau}^n, Y_{i\tau}^n, C_{i\tau}^n)]/Y_{i\tau}^n}{[E_{it}^n / D_{it}^c(E_{it}^n, Y_{it}^n, C_{it}^n)]/Y_{it}^n}\right\};$$

$$D_{STR} = \exp\left\{\sum_{nij} \frac{L(CI_{ij\tau}^n, CI_{ijt}^n)}{L(CI_\tau^n, CI_t^n)} \ln \frac{Y_{i\tau}^n / Y_\tau^n}{Y_{it}^n / Y_t^n}\right\};$$

$$D_{ROS} = \exp\left\{\sum_{nij} \frac{L(CI_{ij\tau}^n, CI_{ijt}^n)}{L(CI_\tau^n, CI_t^n)} \ln \frac{Y_\tau^n / Y_\tau}{Y_t^n / Y_t}\right\};$$

$$
\begin{aligned}
D_{BPC} &= \exp\left\{ \sum_{nij} \frac{L(CI_{ij\tau}^n, CI_{ijt}^n)}{L(CI_\tau^n, CI_t^n)} \ln\left[\frac{BPG_{i\tau}^n}{BPG_{it}^n}\right]^{-1} \right\} \\
&= \exp\left\{ \sum_{nij} \frac{L(CI_{ij\tau}^n, CI_{ijt}^n)}{L(CI_\tau^n, CI_t^n)} \ln\left[BPC_{i(t,\tau)}^n\right]^{-1} \right\}
\end{aligned} ;
$$

$$
\begin{aligned}
D_{EC} &= \exp\left\{ \sum_{nij} \frac{L(CI_{ij\tau}^n, CI_{ijt}^n)}{L(CI_\tau^n, CI_t^n)} \ln \frac{D_{i\tau}^c(E_{i\tau}^n, Y_{i\tau}^n, C_{i\tau}^n)}{D_{it}^c(E_{it}^n, Y_{it}^n, C_{it}^n)} \right\} \\
&= \exp\left\{ \sum_{nij} \frac{L(CI_{ij\tau}^n, CI_{ijt}^n)}{L(CI_\tau^n, CI_t^n)} \ln\left[EC_{i(t,\tau)}^n\right]^{-1} \right\}
\end{aligned} .
$$

$$
CI_{ij,t}^n = C_{ij,t}^n / Y_t; \ Y_t = \sum_n Y_t^n.
$$

In summary, the change in CO_2 intensity at the national level can be attributed to seven indexes: emission factor change, energy mix change, potential energy intensity change, industrial structure change, regional output structure change, the effect of energy technological change, and the effect of energy efficiency change. Each index will contribute to the increase (decline) in CO_2 intensity, if its value is greater (less) than unity. The effects driving the carbon intensity change at the national level (excluding the regional output structure change) are the aggregation of effects obtained at the provincial level. Table 1 summarizes the definitions of the decomposed components.

Table 1. The definitions of the decomposed components.

Symbol	Description
D_{EMF}	the CO_2 emission factor effect
D_{EMX}	the effect of energy mix change
D_{PEI}	the effect of potential energy intensity change
D_{STR}	industrial structure effect, accounting for the impact from output composition change
D_{BPC}	the impact from technological change in energy use
D_{EC}	the effect of energy efficiency change
D_{ROS}	the effect of regional output structure change

3. Empirical Study

3.1. Data

A panel data set including China's 30 provinces during the period of 2006–2012, is collected for the empirical study (Due to data unavailability, Tibet is not included in this study). The economy of each province is divided into six subsectors: "agriculture", "industry", "construction", "transport, storage, and post", "wholesale, retail, hotels, and catering services", and "financial intermediation, real estate, and other tertiary industries" (Generally speaking, for the decomposition model, a high level of sector disaggregation is preferred. Due to data availability, we can divide the entire economy into six subsectors at the most. Because we need a balanced structure of data, multiple dimensions are involved, including time periods, provinces, subsectors, and energy types.). The output variable is represented by the value-added of the industrial subsector. Data on the value-added are collected from the China Premium Database [29]. Data on the energy use by type are obtained from the energy balance tables in the China Energy Statistical Yearbook [30–36]. Data on CO_2 emissions are estimated by the method described in [37]. In the energy balance table, the subsectors consume electricity and heat which do not emit CO_2 directly. However, the generation of electricity and heat mainly consume fuels like coal and oil, thereby emitting CO_2. Such indirect CO_2 emissions, that come from electricity and heat consumption, are also taken into account. We first calculate the electricity/heat emissions factor, which refers to CO_2 emissions for generating per unit of electricity/heat. Then, we calculate the corresponding CO_2 emissions for the electricity and heat consumed by the subsectors. Note, that

unlike other emission factors which are constant, CO_2 emission factors for electricity and heat change over time.

3.2. Decomposition Results

Table 2 presents the decomposition results of CO_2 intensity change in China as a whole, during 2006–2012. As is shown in Table 2, China's CO_2 intensity declined during the research period, with an annual growth rate of −4.4%, and a cumulative growth rate of −23.8%.

Table 2. The change of CO_2 intensity and effects of contributing factors in China.

Year	D_{tot}	D_{EMF}	D_{EMX}	D_{STR}	D_{ROS}	D_{PEI}	D_{EC}	D_{BPC}
2006–2007	0.950	0.984	1.015	1.005	1.000	0.956	1.017	0.974
2007–2008	0.958	0.999	0.999	1.006	1.001	0.957	0.964	1.032
2008–2009	0.935	0.980	0.993	0.979	1.001	0.963	0.999	1.019
2009–2010	0.960	0.991	0.991	1.014	1.001	0.954	0.984	1.026
2010–2011	0.997	1.007	1.043	1.002	1.004	0.995	0.978	0.970
2011–2012	0.936	0.986	0.997	0.988	1.003	0.958	1.009	0.993
Geometric mean	0.956	0.991	1.006	0.999	1.002	0.964	0.992	1.002
2006–2012	0.762	0.946	1.038	0.995	1.010	0.802	0.952	1.013

The decomposition results suggest that D_{PEI} (potential energy intensity change) is the biggest contributor to the decrease of CO_2 intensity, which contributes to a total reduction of 19.8% and 3.6% per year. This finding is in accordance with the results in most literature on the decomposition of CO_2 intensity or CO_2 emissions, illustrating that the decline of energy intensity is the major driving force causing a decrease in CO_2 intensity or CO_2 emissions. Since CO_2 emissions are caused by energy consumption, and the abasement of CO_2 intensity radically depends on the decline of energy intensity, it is not hard to imagine the intimate relationship between CO_2 intensity and energy intensity [8]. In contrast to [8], D_{PEI} in this study is regarded as a hypothetical figure, which measures the impact of energy intensity change on CO_2 intensity, without considering the inefficiency of the energy-usage technology, i.e., the value of potential energy intensity is calculated by excluding the effects from production technology, such as efficiency change and technological change.

D_{EMF} (CO_2 emission factor change) also plays a significant role in declining CO_2 intensity. During 2006–2012, its accumulated effect is calculated as 0.946, which means that it reduced the CO_2 intensity by 5.4%. In this paper, only CO_2 emission factors for electricity and heat change over time. In this sense, the D_{EMF} effect originates from the energy improvement in the sectors of electricity generation and heat generation. D_{EC} (energy efficiency change) is another important driver in the abatement of CO_2 intensity. It shows that China experienced an energy efficiency promotion during 2006–2012, which led to a 4.8% decrease in the CO_2 intensity during the sample period. Conversely, D_{BPC} (energy-saving technology change) had a less significant contribution to the CO_2 intensity reduction. This result is in line with the finding of [24].

In most years, D_{EMX} (energy mix change) marginally contributed to the decrease in CO_2 intensity. However, the opposite impact was seen for the periods of 2006–2007 and 2010–2011. Consequently, in total, it improved the CO_2 intensity by 3.8% during the sample period. This result is consistent with our observation of China's energy consumption. According to [38], the share of coal, the dominant energy in China, has declined very slightly in recent years, but increased in 2007 and 2011. Although the Chinese government has spared no effort to promote industrial upgrade in recent years, it is revealed that the impact of D_{STR} (industrial structure change) on CO_2 intensity is very small. A similar result can be seen for D_{ROS} (regional output structure change). As there were only minimal changes in China's regional economic pattern in past years, China's regional output share was almost unchanged.

Table 3 presents the decomposition results for China's 30 provinces. From Table 3, it can be found that, except for Hainan and Xinjiang, the CO_2 intensity in all of the provinces experienced

a decline during the sample period. Beijing showed the largest reduction of CO_2 intensity (45.5%), which is in line with our expectations, considering Beijing is the capital of China and has the most powerful incentive mechanism to realize its economic growth, based on less energy-intensive industries. Also, a relatively large reduction in CO_2 intensity is observed in the eastern, well-developed cities, such as Shanghai, Tianjin, Guangdong, Zhejiang, and Jiangsu.

Table 3. The change of CO_2 intensity and effects of contributing factors in China's 30 provinces between 2006 and 2012.

Province	D_{tot}	D_{EMF}	D_{EMX}	D_{STR}	D_{PEI}	D_{EC}	D_{BPC}
Anhui	0.712	0.965	0.990	1.146	0.663	0.965	1.017
Beijing	0.545	0.817	1.108	0.931	0.926	0.727	0.960
Chongqing	0.769	0.921	0.967	1.016	0.799	1.028	1.033
Fujian	0.748	0.978	1.039	1.002	0.798	0.903	1.021
Gansu	0.861	1.022	0.950	0.964	0.906	0.988	1.027
Guangdong	0.740	0.943	1.043	0.978	0.865	0.966	0.921
Guangxi	0.776	0.912	1.075	1.129	0.717	0.955	1.024
Guizhou	0.622	0.911	1.009	0.959	0.660	1.019	1.050
Hainan	1.155	1.103	0.965	0.888	1.237	0.986	1.002
Hebei	0.783	0.947	0.963	0.984	0.816	1.062	1.006
Heilongjiang	0.778	0.973	0.990	0.933	0.865	0.961	1.042
Henan	0.680	0.931	1.056	1.028	0.702	0.935	1.026
Hubei	0.744	0.901	0.888	1.053	0.743	1.155	1.029
Hunan	0.646	0.938	1.094	1.081	0.637	0.875	1.045
I-Mongolia	0.893	1.054	1.126	1.091	0.829	0.801	1.039
Jiangsu	0.796	0.966	1.077	0.912	0.903	0.913	1.016
Jiangxi	0.757	0.905	1.137	1.081	0.754	0.889	1.014
Jilin	0.657	0.976	1.080	1.092	0.641	0.887	1.003
Liaoning	0.780	0.980	1.235	1.034	0.787	0.785	1.008
Ningxia	0.901	0.993	1.060	0.956	0.950	0.906	1.041
Qinghai	0.944	0.910	0.983	1.101	0.862	1.073	1.036
Shaanxi	0.768	0.919	0.965	0.993	0.807	1.037	1.042
Shandong	0.758	0.949	1.048	0.926	0.848	0.940	1.033
Shanghai	0.685	0.960	0.998	0.861	0.895	1.051	0.882
Shanxi	0.777	0.985	1.132	0.981	0.803	0.858	1.031
Sichuan	0.688	0.785	0.880	1.099	0.678	1.323	1.012
Tianjin	0.633	0.990	0.859	0.962	0.756	1.035	0.990
Xinjiang	1.216	1.012	1.195	0.954	1.250	0.809	1.042
Yunnan	0.820	0.973	1.034	0.928	0.896	0.949	1.032
Zhejiang	0.724	0.913	0.995	0.952	0.818	0.994	1.030

D_{PEI} (potential energy intensity change) was the dominant driver of the decline of CO_2 intensity in all of the provinces, except Hainan and Xinjiang. The value of D_{PEI} ranges from 0.637 to 1.25, with an average value of 0.816. Hunan demonstrated the best performance in terms of D_{PEI}, followed by Jilin and Guizhou. Conversely, Hainan and Xinjiang suffered from an increase in D_{PEI}, which was the dominant factor for the increase of CO_2 intensity.

As was identified at the national level, the effects of D_{STR} (industrial structure change) at the provincial level are relatively small, ranging from 0.861 to 1.146, with an average value of 0.998. It can also be seen that, for all of the provinces except Fujian in the eastern area, D_{STR} (industrial structure change) contributed to the reduction of CO_2 intensity. Among them, Shanghai showed the largest impact from D_{STR} (industrial structure change), which reduced its CO_2 intensity by 13.9%. For Shanghai, during the sample period, the output share of energy intensive sectors decreased from 47% to 39%, which consequently induced the decline of its carbon intensity. On the contrary, D_{STR} (industrial structure change) increased the CO_2 intensity in most provinces of the central and western areas. Anhui, Guangxi, and Qinghai were ranked at the bottom of the table. This is because the industrial sector in these provinces expanded rapidly during the time period used in this study.

Among the 30 provinces, 26 registered a value of D_{EMF} that was smaller than unity, indicating that D_{EMF} (CO_2 emission factor change) was another important contributor to the reduction of CO_2 intensity in China's provinces. Sichuan registered the lowest value (0.785), followed by Beijing (0.817) and Hubei (0.901). Sichuan and Hubei are abundant in terms of hydropower resources. The development of hydropower substituted coal consumption. In order to improve the air quality, Beijing carried out a "changing coal into gas" project, which significantly reduced coal consumption. A similar case can be found in D_{EC} (energy efficiency change). Among the 30 provinces, 21 registered a value of D_{EC} that was smaller than unity. This means that most of the provinces experienced an improvement in the energy use efficiency. Beijing demonstrated the best performance, with a D_{EC} value of 0.727, indicating that it brought about a 27.3% reduction of CO_2 intensity during the sample period.

With regards to the impact of D_{BPC} (energy-saving technology change), only four provinces, Shanghai (0.882), Guangdong (0.921), Beijing (0.96), and Tianjin (0.99) had a positive contribution of energy-saving technology on the reduction of CO_2 intensity. No surprisingly, they are the most developed provinces in China. Our result reveals that they had a relatively higher capability for innovating advanced energy technology. For other provinces, the change of energy-saving technology did not contribute to a reduction in the CO_2 intensity during the sample period.

3.3. The Potential CO_2 Intensity Reduction

The decomposition results help us understand the determination of CO_2 intensity in China. This subsection further measures the potential CO_2 intensity reduction in China, using the PCII (potential values for CO_2 intensity improvement) index proposed by [24].

The PCII for region *n* at the time period *t* under the contemporaneous technology scenario can be defined as:

$$PCII_{t,c}^n = CI_t^n - CI_{t,bpc}^n$$
$$CI_{t,bpc}^n = \sum_{ij} \frac{C_{ij,t}^n}{E_{ij,t}^n} \frac{E_{ij,t}^n}{E_{i,t}^n} \frac{E_{i,t}^n / D_i^c(E_{i,t}^n, Y_{i,t}^n, C_{i,t}^n)}{Y_{i,t}^n} \frac{Y_{i,t}^n}{Y_t^n} \tag{13}$$

The PCII for region *n* at the time period *t* under the global technology scenario can be defined as:

$$PCII_{t,g}^n = CI_t^n - CI_{t,bpg}^n$$
$$CI_{t,bpg}^n = \sum_{ij} \frac{C_{ij,t}^n}{E_{ij,t}^n} \frac{E_{ij,t}^n}{E_{i,t}^n} \frac{E_{i,t}^n / D_i^g(E_{i,t}^n, Y_{i,t}^n, C_{i,t}^n)}{Y_{i,t}^n} \frac{Y_{i,t}^n}{Y_t^n} \tag{14}$$

Similarly, the PCII for the whole country during the time period *t*, under the contemporaneous technology and the global technology, can be defined as Equations (15) and (16), respectively.

$$PCII_{t,c} = CI_t - CI_{t,bpc}$$
$$CI_{t,bpc} = \sum_{nij} \frac{C_{ij,t}^n}{E_{ij,t}^n} \frac{E_{ij,t}^n}{E_{i,t}^n} \frac{E_{i,t}^n / D_i^c(E_{i,t}^n, Y_{i,t}^n, C_{i,t}^n)}{Y_{i,t}^n} \frac{Y_{i,t}^n}{Y_t^n} \frac{Y_t^n}{Y_t} \tag{15}$$

$$PCII_{t,g} = CI_t - CI_{t,bpg}$$
$$CI_{t,bpg} = \sum_{nij} \frac{C_{ij,t}^n}{E_{ij,t}^n} \frac{E_{ij,t}^n}{E_{i,t}^n} \frac{E_{i,t}^n / D_i^g(E_{i,t}^n, Y_{i,t}^n, C_{i,t}^n)}{Y_{i,t}^n} \frac{Y_{i,t}^n}{Y_t^n} \frac{Y_t^n}{Y_t} \tag{16}$$

The potential CO_2 intensity reduction for the whole of China during 2006–2012 is presented in Figure 1. It shows a descending trend, suggesting that China was narrowing the room for CO_2 intensity reduction year by year. In 2006, China's potential CO_2 intensity reduction was 83.7 thousand tons per billion RMB (2005 price) under the contemporaneous technology scenario, while in 2012, this number decreases by nearly 30 percent, which is only 59.1 thousand tons per billion RMB (2005 price). Mainly due to the decrease of the potential energy intensity, China's potential CO_2 intensity reduction drops by an average of 4.5% a year during 2006–2012. Compared to the potential reduction under the

contemporaneous technology scenario, the figures under the global technology scenario are 20%–30% higher, suggesting that there is a considerable distance between contemporaneous technology and global technology. As a result, technological improvement is an ideal way to further narrow the room for CO_2 intensity reduction.
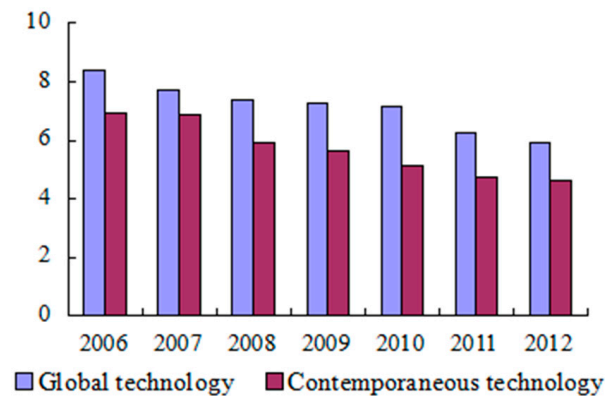

Figure 1. The potential CO_2 intensity reduction for China: 2006–2012. Unit: 10 thousand tons/billion RMB (2005 price).

To conserve space, we only report the potential CO_2 intensity reduction for China's 30 provinces in 2012, shown in Figure 2. The potential CO_2 intensity reduction is much higher in poorer western provinces, when compared to other provinces in China. Under the contemporaneous technology scenario, the potential CO_2 intensity reduction in the western provinces, such as Guizhou, Qinghai, Shanxi, Xinjiang, and Ningxia, is 201.9, 164.5, 158.2, 154.6 and 150.8 thousand tons per billion RMB (2005 price), respectively, while the potential CO_2 intensity reduction in the eastern provinces, such as Shanghai, Zhejiang, Jiangsu, Guangdong, and Beijing, is merely 21.3, 17.2, 17.0, 14.1 and 9.3 thousand tons per billion RMB (2005 price), respectively. This implies that there is a large potential for CO_2 intensity reduction in China's western provinces.

It can also be observed that the potential abasement of CO_2 intensity under the global technology scenario is larger than that under the contemporaneous technology scenario. Moreover, the gap of potential reduction in CO_2 intensity between the two different scenarios is larger in China's poorer western provinces. In those western provinces such as Guizhou, Qinghai, Xingjiang, and Ningxia, the amount of potential CO_2 intensity reduction under the global technology scenario is 164.1, 124.3, 119.6 and 82.2 thousand tons per billion RMB (2005 price), respectively; being 37.8, 40.3, 35.0, 68.6 and 41.0 thousand tons per billion RMB (2005 price) higher than those under the contemporaneous technology scenario. In contrast, in the eastern provinces such as Beijing, Guangdong, Jiangsu, Zhejiang, and Shanghai, the potential CO_2 intensity reduction under the global technology scenario is 7.1, 9.4, 8.9, 8.2 and 17.7 thousand tons per billion RMB (2005 price), respectively; being merely 2.2, 4.7, 8.0, 9.1, 3.5 thousand tons per billion RMB (2005 price) higher than those under the contemporaneous technology scenario. That is because the eastern provinces are better off, and are more likely to absorb external technologies or invent advanced energy-saving technologies.
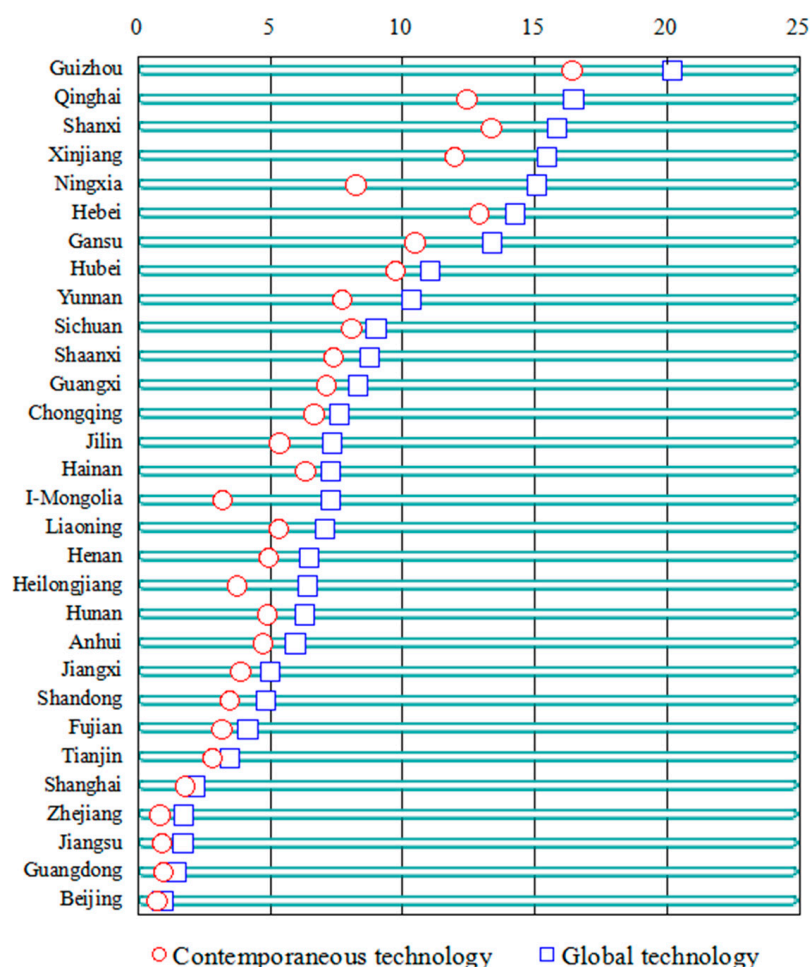
Figure 2. The potential CO_2 intensity reduction for China's 30 provinces in 2012. Unit: 10 thousand tons/billion RMB (2005 price).

4. Conclusions

The Chinese government considers CO_2 intensity to be one of the most important references for designing its energy and environmental policies. Understanding and analyzing the driving factors of CO_2 intensity in China and its regions, are therefore of vital importance. An increasing number of research papers place an emphasis on analyzing the factors influencing China's CO_2 intensity. However, very few of them have paid attention to the variation in China's regions. To the best of our knowledge, this paper is the first attempt to explore the change of CO_2 intensity in China, as well as in its provinces. To serve this purpose, we propose a modification of the decomposition model of Kim and Kim [24], which integrates the strengths of IDA and PDA. Moreover, we also calculate the potential reduction of CO_2 intensity for China as a whole and its provinces. Using a panel data set including China's 30 provinces during the period of 2006–2012, empirical analysis is conducted and meaningful results are obtained accordingly.

With regards to China as a whole, D_{PEI} (potential energy intensity change) was the dominant driving factor of the decrease in CO_2 intensity, which contributed to a total reduction of 19.8% and 3.6% per year. D_{EMF} (CO_2 emission factor change), D_{EC} (energy efficiency change), and D_{STR} (industrial structure change) were also contributing factors to the abatement of CO_2 intensity. By contrast, D_{BPC} (energy-saving technology change) and D_{EMX} (energy mix change) did not lead to a decrease in CO_2 intensity.

When it comes to the provincial level, some mixed pictures emerge. CO_2 intensity in all of the provinces, excluding Xinjiang and Hainan, exhibited a decrease in CO_2 intensity during the period of

2006–2012. For these provinces, the CO_2 intensity reduction was mainly driven by D_{PEI} (potential energy intensity change). D_{EC} (energy efficiency change) and D_{EMF} (CO_2 emission factor change) also played positive roles in the CO_2 intensity reduction for most provinces. The best performers in D_{PEI}, D_{EC}, and D_{EMF}, were Hunan (0.637), Beijing (0.727), and Sichuan (0.785), respectively. Only four provinces, Shanghai (0.882), Guangdong (0.921), Beijing (0.96), and Tianjin (0.99), had positive contributions of energy-saving technology for the reduction of CO_2 intensity, which suggests that the Chinese government should promote technology diffusion among the regions, helping those which are less developed to also introduce advanced technology.

In terms of the CO_2 intensity reduction potential, China showed a narrowing possibility year by year. In 2012, the potential reduction under the global technology and the contemporaneous technology scenarios are calculated as 59.1 and 46.0 thousand tons per billion RMB (2005 price), decreasing from 83.7 and 69.3 thousand tons per billion RMB (2005 price), respectively. The provincial variations are also presented. Provinces in the western area generally showed a relatively large potential reduction for CO_2 intensity, while those in the eastern area evidenced a small amount.

Finally, it should be pointed out that this paper focuses on exploring change in China's carbon intensity using a decomposition method. We attribute the change of carbon intensity to several predefined effects. However, we have not answered the question of what drives the change of the decomposed components. This question requires great efforts in developing a unified model with economic foundations and collecting more related data. It should be further analyzed in future studies.

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