Nature Environment and Pollution Technology
An International Quarterly Scientific Journal

ISSN: 0972-6268 | Vol. 14 | No. 4 | pp. 827-832 | 2015

Original Research Paper

Study on Carbon Dioxide Emission Performance in the Guangdong Province Based on the Malmquist-Luenberger Index

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Nat. Env. & Poll. Tech.
Website: www.neptjournal.com
Received: 17-09-2015
Accepted: 20-10-2015

Key Words:
Carbon dioxide
Emission performance
Environmental damage
Pollution control

ABSTRACT

Based on academic studies of carbon dioxide emissions, an environmental data envelopment analysis (DEA) model, including undesirable carbon dioxide emissions, is reported here. MaxDEA software was used to calculate carbon emissions performance in the Guangdong Province of China. Our findings revealed that in order to achieve the same level of economic development achievements, carbon emission performance and carbon dioxide pollution are negatively correlated. Moreover, pollution prevention and protection measures can decrease the degree of carbon dioxide pollution. Here, we observed that increasing economic development has a positive effect on carbon emission performance and the greater the energy demand, the higher the degree of pollution. Technological change is a decisive factor influencing carbon emissions performance. By employing technological innovations, energy utilization efficiency and the resulting level of environmental pollution can be greatly improved.

INTRODUCTION

The global climate change issue has attracted widespread attention around the world. In 2009, the Copenhagen Accord was agreed to at the United Nations Framework Convention on Climate Change, in Copenhagen. This accord was widely referred to as "Our last chance to save humanity." Since 1978, the Guangdong Province has made remarkable economic advancements. At the same time, however, gradually increasing carbon emissions in the province have attracted the Government's attention. The relationship between carbon emissions and carbon dioxide pollution is closely related. The Government should establish a regulatory framework treating carbon dioxide emissions as pollution, and set goals for reduction in energy use and pollution emissions. Moreover, the Guangdong provincial Government has committed to decreasing the province's carbon dioxide emissions per unit of GDP by 35% by 2015 and 45% by 2020 from the 2005 levels. It is therefore urgent that the province explores a low carbon emissions development path.

As scientific research into carbon emissions has expanded in recent years, climate scientists have come to see global climate change as an increasingly urgent threat (Stocker 2013). During the 20th century, atmospheric concentrations of key greenhouse gases increased due to human activities. The severity of climate change brought about by human activities depends both on the magnitude of the change and on the potential of the irreversibility of this change. For example, climate change that is a result of increases in atmospheric carbon dioxide concentration has been reported to be irreversible for 1,000 years after the emissions stop (Solomon et al. 2009). The climate in southwestern North America, an area defined as the western Great Plains to the Pacific Ocean, would become more arid throughout the current century as a consequence of rising greenhouse gases (Seager & Vecchi 2010). Other scholars have indicated that new diplomatic strategies are needed; suggestions have been made that diplomats focus on pollutants other than carbon dioxide, such as soot, that would be easier to regulate in the international community (Burney et al. 2013). An integrated energy-economy-climate modelling system was used to examine how further delay of cooperative action and the availability of technology impact the challenges of mitigating climate change. With comprehensive emissions reductions starting after 2015 and the full availability of technology, they estimated the maximum warming experienced in 21st century may be limited to less than a two centigrade degrees change, with moderate economic impacts (Bertram et al. 2013). Understanding how decrease in CO_2 emissions would influence global temperatures had been hampered in recent years by confusion regarding issues of continued warming and irreversibility. Further misunderstandings may stem from recent studies indicating that warming has already occurred, as a result of past anthropogenic carbon dioxide increases, and it is irreversible on a time scale of at least 1000 years. However, the irreversibility of past changes does not mean that further warming is unavoidable (Matthews & Solomon 2013). Some scholars conducted the researches on allocation scheme of energy consumption, and indicated the ultimate allocation scheme of national energy consumption which was obtained by comprehensively considering the original energy consumption of the base year and the increment allocation of the expected year, and the fair interval for energy consumption allocation could ensure the equity on energy allocation effectively (Li et al. 2014).

By conducting a sustainability assessment of carbon emissions, energy use, and water withdrawal in US manufacturing sectors, some scholars indicated the eco-efficiency scores of most industrial sectors were low (Egilmez et al. 2014). The total factor carbon emission performance was improved mainly by technological advancements (Zhou et al. 2010, Sueyoshi et al. 2013). Furthermore, economic growth and changes in transportation energy usage were the main factors driving increased CO_2 emissions (Timilsina & Shrestha 2008). And, the logarithmic mean divisia index (LMDI) decomposition methodology was widely used in this study field (Gonzalezn & Martinez 2012, Mahony et al. 2007). Academic studies on carbon emission performance have mainly focused on total energy carbon emissions and industry characteristics. In addition, studies have tended to target the relationship between any two of the following three factors: economic development, energy consumption, and carbon dioxide emissions. To date, no comprehensive studies examining the relationship between all three of these factors have been reported. Even though many studies consider the mechanisms and dynamic factors governing carbon emissions, they are limited to macro investigations, and few studies exist that evaluate specific industries separately.

DEA MODEL AND MALMQUIST-LUENBERGER INDEX

The DEA method was proposed in 1978 (Charnes et al. 1978). Assuming that there are *m* input indexes, *s* desirable outputs, and *k* undesirable outputs in an economic system, the specific expression is as follows: The input index value of *j* sample is *Xj*, the desirable output index value is *Yj*, and the undesirable index output value is *Uj*. The DMU (Decision Making Units) is established, and the model for the undesirable output emission efficiency DMUd is as follows:

$$
\begin{aligned}
& Min\lambda_d \\
& s.t. \\
& \sum_{j=1}^{n} z_i X_i \le X_d \\
& \sum_{j=1}^{n} z_i Y_i \le Y_d \\
& \sum_{j=1}^{n} z_i U_i = \lambda_d U_d \\
& z_i \ge 0, j = 1, 2 \ldots n
\end{aligned} \quad \ldots(1)
$$

The above model is aimed at finding an optimal production combination for DMU through minimizing λd, in order as to establish the efficiency level of the production combination.

The Malmquist index was used to calculate productivity changes in 1982 (Caves et al.1982). As the DEA model can only be used to measure cross-section data, later scholars used the Malmquist index together with a DEA model to measure cross-section data and study dynamic changes in productivity.

Assuming that there are *m* DMUs and *n* inputs for each DMU, one output at stage t is obtained;

$$X_j^t = \left(x_{1j}^t, x_{2j}^t, \ldots x_{nj}^t \right)^T \quad \ldots(2)$$

X_j^t represents the input value of *j* DMU at stage t, t=1, 2,……,T

$$Y_j^t = \left(y_{1j}^t, y_{2j}^t, \ldots y_{nj}^t \right)^T \quad \ldots(3)$$

Y_j^t represents the output value of *j* DMU at stage t, t=1, 2,……,T

Under CCR, the distance function of $\left(X^t, Y^t\right)$ at stage t is $D_c^t\left(X^t, Y^t\right)$, the distance function of $\left(X^t, Y^t\right)$ at stage t+1 is, $D_c^{t+1}\left(X^t, Y^t\right)$, the distance function of $\left(X^{t+1}, Y^{t+1}\right)$ at stage t is $D_c^t\left(X^{t+1}, Y^{t+1}\right)$, and the distance function of $\left(X^{t+1}, Y^{t+1}\right)$ at stage t+1 is $D_c^t\left(X^{t+1}, Y^{t+1}\right)$.

The Malmquist-Luenberger index was used for free disposal of desirable outputs and weak disposal of undesirable outputs (Chung et al. 1997), and the ML productivity indexes from stage t to t+1 are as follows:

$$ML_t^{t+1} = \left\{ \frac{1 + \vec{D}_c^t\left(x^t, y^t, b^t; y^t, -b^t\right)}{1 + \vec{D}_c^t\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)} * \frac{1 + \vec{D}_c^{t+1}\left(x^t, y^t, b^t; y^t, -b^t\right)}{1 + \vec{D}_c^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)} \right\}^{\frac{1}{2}} \quad \ldots(4)$$

Using information from the Guangdong Statistical Yearbook, the Guangdong Province was divided into four main

Table 1: Carbon emission performance evaluation system.

Input indicator	Output indicator
Fixed capital (K) Labour force input (L) Primary energy consumption (E)	GDP (Y) Carbon dioxide emissions (C)

regions: the Pearl River Delta, Eastern, Western, and Northern regions. The Pearl River Delta region includes the cities of Guangzhou, Shenzhen, Dongguan, Foshan, Zhongshan, Zhuhai, Jiangmen, Huizhou and Zhaoqing; the Eastern region includes the cities of Chaozhou, Shantou, Jieyang and Shanwei; the Western region includes the cities of Zhanjiang, Maoming and Yangjiang; and the Northern region includes the cities of Shaoguan, Qingyuan, Heyuan, Meizhou and Yunfu. The environmental DEA index system adopted is slightly amended on the basis of the international carbon dioxide performance indicator evaluation system, and fixed capital replaced capital stock (Table 1).

The aforementioned environmental DEA model can be used to build a linear programming model as follows:

$$\begin{aligned} & Min\lambda_d \\ & s.t. \\ & \sum_{j=1}^{n} z_i K_i \le K_d \\ & \sum_{j=1}^{n} z_i L_i \le L_d \\ & \sum_{j=1}^{n} z_i E_i \le E_d \\ & \sum_{j=1}^{n} z_i Y_i \ge Y_d \\ & \sum_{j=1}^{n} z_i C_i = C_d \\ & z_i \ge 0, j = 1, 2...n \end{aligned} \qquad ...(5)$$

The fixed capital, labour force input, GDP and primary energy consumption data used in this investigation were taken from the Guangdong Statistical Yearbook (2005-2012) and the statistical yearbooks of the prefecture level cities in the Guangdong Province. Energy consumption is multiplied by the emission factor released by IPCC to calculate energy carbon emissions.

RESULTS AND DISCUSSION

Calculation of carbon emission performance: MaxDEA software was used for data analysis. The carbon emission performances in designated cities of the Guangdong Province during an eight year period are given in Table 2.

The static efficiencies of the cities Guangzhou, Shenzhen, Zhuhai, Shanwei, Maoming and Chaozhou are effective, which suggests that these cities can maximize utilization of the environmental cost to carry out economic production, and at the same time reduce the levels of carbon dioxide pollution produced. However, other reasons can explain the static efficiencies of these cities. Guangzhou, Shenzhen and Zhuhai are economically developed areas with higher energy efficiency, and carry out vigorous environmental conservation efforts to reduce carbon dioxide pollution. Shanwei, Maoming and Chaozhou are less developed areas in Guangdong, where heavy industry is not yet developed; therefore there are lower levels of energy consumption and carbon emissions in these cities.

Calculation and analysis of the Malmquist-Luenberger index: The Malmquist index was first used to measure productivity changes. However, the index does not take undesirable outputs into consideration. The Malmquist-Luenberger index, on the other hand, allows for the existence of undesirable outputs without information on shadow prices, so it can provide dynamic efficiency evaluations for production departments where undesirable outputs exist. The ML index can be decomposed into technological efficiency (TE) and technological change (TC).

From the ML index and its decomposition data, the average value of total factor productivity of the Guangdong Province showed an increasing trend, with peaks in 2007 and 2011 (Table 3). Overall, the annual mean of the ML index is 1.03, we can see that the annual growth rate of the total factor productivity was maintained at 3%. These results can be explained by the development of energy saving technology, the widespread use of new energy sources, the efficiency of energy utilization gradually improving, and the quality of economic development continually improving in the Guangdong region. Therefore, the environmental utilization cost per unit of GDP continued to decrease, while the damage to the environment continued to lessen.

The average annual increase in the total factor productivity of the four regions, in descending order, is the Pearl River Delta region > the Western region > the Eastern region > the Northern region. The order of technological change is the Pearl River Delta region > the Western region > the Eastern region > the Northern region (Table 4). Both results are consistent with economic development levels.

The Pearl River Delta region is in a period of post industrialization. The region has completed the transition from industrialization, including upgrading regional industries. Some of the high energy consumption, high pollution, and

Table 2: Carbon emission performance in cities of the Guangdong Province.

	2005	2006	2007	2008	2009	2010	2011	2012
Guangzhou	1	1	1	1	1	1	1	1
Shenzhen	1	1	1	1	1	1	1	1
Zhuhai	1	1	1	1	1	1	1	1
Shantou	1	1	1	0.99	1	1	0.943	0.91
Foshan	0.839	0.891	0.961	0.903	0.92	0.922	0.911	0.902
Shaoguan	0.708	0.703	0.714	0.689	0.691	0.693	0.704	0.706
Heyuan	0.831	0.867	0.84	0.919	1	1	1	1
Meizhou	0.82	0.881	0.937	0.939	1	0.985	1	1
Huizhou	0.839	0.805	0.787	0.796	0.787	0.794	0.794	0.789
Shanwei	1	1	1	1	1	1	1	1
Dongguan	0.866	0.83	0.81	0.825	0.83	0.831	0.829	0.822
Zhongshan	0.854	0.866	0.876	0.89	0.894	0.89	0.9	0.9
Jiangmen	0.862	0.85	0.844	0.853	0.855	0.846	0.838	0.84
Yangjiang	1	1	1	1	1	1	0.919	0.905
Zhanjiang	1	0.993	0.988	1	0.982	0.963	0.993	0.978
Moming	1	1	1	1	1	1	1	1
Zhaoqing	0.826	0.82	0.819	0.826	0.824	0.824	0.843	0.84
Qingyuan	0.69	0.685	0.693	0.699	0.694	0.693	0.707	0.737
Chaozhou	1	1	1	1	1	1	1	1
Jieyang	0.892	0.842	0.838	0.835	0.816	0.815	0.824	0.826
Yunfu	1	1	1	1	0.811	0.802	0.744	0.749

high emission industries have begun to transfer to other regions. In addition, the Pearl River Delta region attaches great importance to environmental protection; therefore, its ML index is the highest.

Both the Western and Eastern regions are still in an industrialization stage; therefore, industrial restructuring, energy saving technology and environmental protection awareness are still in flux. The Northern area had the lowest ML index; a result of the economic development in the region being low, and the GDP scale being small.

Analysis of influencing factors: The carbon emission performance index, its changes and regional features have been analyzed above; however, the underlying causes of these changes and differences have not been explained. For this reason, further analysis of the correlated variables was conducted. An accumulated Malmquist-Luenberger carbon emission performance index was used as the dependent variable for the study, and the independent variables (Table 5) were defined as follows.

Industrial structure (STR): ratio of secondary sector output to the gross regional product of an individual city in a given year.

Energy intensity (EI): ratio of total energy consumption to GDP.

Economic development level (ED): ratio of annual gross regional product to total population of the region.

Urbanization level (UL): ratio of urban population to total population in the same period.

The level of opening up economy (OP): ratio of total imports and exports to GDP.

ML stands for the Malmquist-Luenberger carbon emission performance index for a given city, accumulated over the years examined.

α stands for constant terms, and ε stands for random variables.

$$ML = \alpha + \beta_1 STR + \beta_2 EI + \beta_3 ED + \beta_4 UL + \beta_5 OP + \varepsilon \quad ...(6)$$

From the empirical results, we found that STR and ED had a significant positive effect on ML in the Pearl River Delta region; while EI and UL had a negative impact. These data are due to the manufacturing industry in the Pearl River Delta region, which is application of energy saving and emission reduction technology, and with the scale effect on economic development, these factors enhance carbon emission performance, and reduce environmental damage.

It is evident from Table 6 that economic development levels had a significant positive effect on carbon emission performance in these three regions; urbanization levels had a negative effect on carbon emission performance in the Western and Eastern regions. Energy intensity had a significant negative effect on the Pearl River Delta, Western, and Northern regions; these findings are consistent with research conclusions reported by other scholars. The greater the energy intensity the higher the degree of pollution, thus it is necessary to vigorously promote the application of clean energy

Table 3: Changes and decomposition of the annual average Malmquist-Luenberger index of the Guangdong Province.

	EC	TC	ML
2006	0.994	1.032	1.025
2007	1.002	1.038	1.041
2008	1.004	1.028	1.032
2009	0.997	1.016	1.013
2010	0.998	1.02	1.018
2011	1.007	1.063	1.07
2012	0.986	1.022	1.009
Geometric mean	0.998	1.031	1.03

Table 4: Comparison of average annual indexes of the four regions.

Region	EC	TC	ML
Pearl River Delta region	1	1.039	1.039
Eastern region	0.996	1.028	1.024
Western region	0.990	1.035	1.025
Northern region	1.002	1.018	1.020
Guangdong	0.997	1.03	1.027

Table 5: Regression analysis of carbon emission performance in the Pearl River Delta region.

	Coefficient	Std.error	z	Prob.
STR	3.664	1.078	3.4	0.001***
EI	-2.638	1.064	-2.48	0.013**
ED	0.416	0.079	5.3	0.000***
UL	-5.794	0.980	-5.91	0.000***
OP	-0.180	0.138	-1.31	0.190
_cons	4.467	1.057	4.23	0.000

*~p<0.1; **~p<0.05; ***~p<0.01

Table 6: Regression analysis of carbon emission performance in the Eastern, Western and Northern regions.

	Eastern region		Western region		Northern region	
	Prob.	Coefficient	Prob.	Coefficient	Prob.	Coefficient
STR	0.003***	-5.851	0.485	-3.113	0.328	-2.316
EI	0.633	-0.130	0.014**	-1.423	0.037**	-3.107
ED	0.000***	2.095	0.000***	1.185	0.000***	2.836
UL	0.000***	-5.356	0.063*	-7.774	0.285	-2.168
OP	0.307	-0.028	0.958	0.113	0.065*	-0.400
_cons	0.000	5.023	0.016	5.277	0.103	-4.414

*~p<0.1; **~p<0.05; ***~p<0.01

sources to further improve carbon emission performance.

The industrial structure had a significant positive effect on the Pearl River Delta region. This is because of a majority of the cities in this region have progressed to the middle and/or later stages of industrialization, which means energy saving technology has been widely adopted in the manufacturing industry. Following an increase in size in the manufacturing industry, its contribution to desirable outputs is much greater than to undesirable outputs. Conversely, cities in the Eastern region are still in the early or middle stages of industrialization, they need to put forth greater efforts to promote the development of major energy saving and emission reducing projects and to make widespread use of low carbon and energy saving engineering technologies.

The level of urbanization displayed a significant negative effect on carbon emission performance in the Pearl River Delta, Eastern, and Western regions, and the degree of opening-up had a significantly negative effect on carbon emission performance in the Northern regions. Therefore, it is necessary to actively explore and develop a new type of urbanization in China to reduce damage to the environment caused by the urbanization process.

CONCLUSIONS

Here, an environmental DEA model was employed and a Malmquist carbon emission performance index was constructed, using a total framework factor, in order to conduct an empirical study on carbon emission performances, regional differences, and influencing factors, in 21 prefectural level cities in the Guangdong Province, between the period of 2005-2012. The research findings indicate the following:

The dynamic carbon emission performance in the Guangdong Province exhibited an upward trend, the contribution of technological change to carbon emission performance is greater than that of technological efficiency, and technological change was a decisive factor influencing total factor productivity.

In respect to maintaining the same level of economic development advancements, carbon emission performance and carbon dioxide pollution were negatively correlated. Furthermore, pollution prevention and protection measures can improve the degree of carbon dioxide pollution. The level of economic development had a positive effect on the carbon emission performance, and the greater the energy intensity the higher the degree of pollution. These findings clearly demonstrate that strengthening technical innovations can actively improve energy utilization efficiency and reduce environmental pollution.

ACKNOWLEDGEMENT

This research has been financed by the “Theoretical Guangdong Team” project 2013 (LLYJ1310)

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