

Carbon Efficiency, Carbon Reduction Potential, and Economic Development in the People's Republic of China

A Total Factor Production Model



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People's Republic of China**
A Total Factor Production Model

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Asian Development Bank

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Abstract

The most commonly used measure of the carbon performance of an economy is carbon intensity (carbon dioxide per gross domestic product [CO_2/GDP]). As an indicator, it is easy to understand and use, but it has serious limitations. First, it is incapable of capturing the multidimensional features of an economy's carbon performance, as economies are endowed with different natural resources and factors of production. Second, it cannot measure the substitution effects between energy and other factors. It may increase solely because energy is substituting for labor, rather than due to any underlying deterioration in emitting technology. This can happen in any modernization process of any economy. Other factors, such as changes in the energy mix or sectoral changes in an economy, can also cause movements in carbon intensity that do not represent actual changes in carbon performance. This paper therefore suggests that we consider economy-wide carbon performance from a total factor production perspective. Based on the lessons learned from the efficiency analysis literature, this paper proposes a new approach that relies on a Data Envelopment Analysis (DEA)-based model. The paper presents the findings of an empirical study that was conducted using provincial-level data from the People's Republic of China in 2005. The findings not only contribute to the research methodology, but may also have important implications for national and international climate change policies.

Key words: Carbon efficiency, Carbon reduction potential, Economic development

Abbreviations

CNY	–	yuan
CO_2	–	carbon dioxide
DEA	–	Data Envelopment Analysis
DMU	–	decision-making unit
GDP	–	gross domestic product
MCI	–	Modified Carbon Intensity
PRC	–	People's Republic of China

Introduction

The People's Republic of China (PRC) is the world's second-largest energy consumer after the United States and has one of the world's fastest-growing energy sectors. While energy fuels economic growth and poverty reduction, inefficient energy use accelerates resource depletion and severely damages the environment. It is hard to reconcile continued energy consumption growth with environmental sustainability. The government has made great efforts to improve energy efficiency and reduce carbon dioxide (CO₂) emissions. For example, its Eleventh Five-Year Plan (2006–2010) mandates a 20% reduction by 2010 in the energy intensity,¹ which has been allocated to the provinces, autonomous regions, and municipalities. The government has earmarked 10 key industries for energy savings, and has placed under tight supervision 1,000 energy-intensive enterprises. In 2006, the government introduced its National Evaluation Report on Climate Change, which included plans to develop a low-carbon economy. In September 2007, the government declared that the PRC would promote a low-carbon economy by improving energy efficiency, developing low-carbon energy technology, expanding carbon sinks,² and developing renewable energy.³ In November 2009, the government announced that it would reduce by 2020 the PRC's carbon intensity⁴ by 40%–45% from the level in 2005.⁵ These steps have been recognized as signs of a strong political commitment by the government to developing a low-carbon economy.

Combating climate change requires the international community to work together to reduce the total amount of CO₂ emissions globally, ultimately stabilizing its atmospheric concentration at a level that would prevent dangerous anthropogenic interference with the climate system. Achieving this target would require great improvements in the carbon performance of all economies. However, despite continuing interest among academics and policy makers, there have been few in-depth examinations of economy-wide carbon performance. Currently, the most commonly used measure of an economy's carbon performance is carbon intensity, an indicator that is easy to understand and use, but that has many serious limitations. First, carbon intensity is incapable of capturing multidimensional features of an economy's carbon performance. As stipulated in the Copenhagen Accord, combating climate change needs to be considered "...on the basis of equity and in the context of sustainable development" (para. 1, Copenhagen Accord, 2009). In most countries, CO₂ emissions come mainly from the consumption of fossil energy. However, energy alone cannot produce anything; it must be combined with other factors of production, such as capital and labor, to produce output. Countries are at different stages of development, and

¹ The amount of energy consumed per unit of gross domestic product (GDP).

² A carbon sink is a natural or artificial feature, such as a forest, that absorbs and stores carbon, thereby removing it from the atmosphere.

³ President Hu Jintao made this declaration at the 15th Asia-Pacific Economic Cooperation conference in Sydney, Australia on 8 September 2007.

⁴ The amount of carbon emitted per unit of GDP.

⁵ The announcement was made on 26 November 2009 as a sign of the PRC's commitment to addressing global climate change.

they are endowed with different natural resources and factors of production. They therefore take different paths when it comes to economic growth. The multidimensional features of these different paths cannot be explained by this simple ratio (CO_2/GDP). Second, this ratio cannot measure the substitution effects between energy and other factors. For example, the carbon intensity of an economy may increase solely because energy is replacing labor, rather than due to any underlying deterioration in emitting technology. This can happen in any modernization process of any economy. Other factors, such as energy-mix or sectoral changes in an economy, can also cause movements in carbon intensity that do not represent actual changes in carbon performance. For these reasons, carbon intensity can sometimes be a

meaningless yardstick for comparing mitigation and adaptation activities across countries. For example, to produce the same amount of output, a country endowed with less carbon-intensive energy resources might emit much lower CO_2 emissions than another country endowed with carbon-intensive resources, no matter how hard the latter may be trying to reduce the energy consumption (measured in thermal units) of its production processes.

Therefore, there is a need to examine economy-wide carbon performance carefully. The purpose of this paper is to address this issue and propose a new concept of "carbon efficiency" that uses a total factor production model based on Data Envelopment Analysis (DEA).

Research Methodology

Literature Review

Efficiency analysis plays a significant role in assessing the performance of a decision-making unit (DMU) in relation to the best practice. Modern efficiency analysis begins with Farrell (1957), who first introduced measures of the production efficiency of a DMU relative to the best-practice frontier constructed by sample data. Data Envelopment Analysis (DEA) is a linear programming technique using a piecewise linear convex hull to estimate the efficiency frontier. Since Charnes et al. (1978), DEA has been used extensively to conduct efficiency analyses.

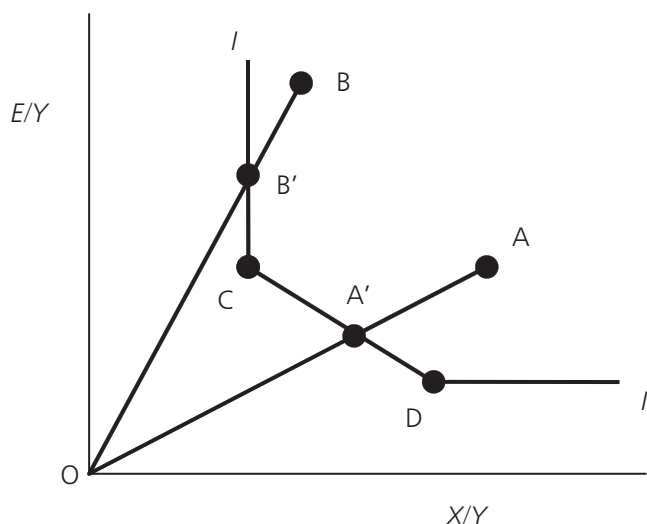
Zhou et al. (2008) reported that there has been an increasing number of energy and environmental studies using DEA. On the topic of energy efficiency, DEA has gradually gained popularity in both micro- and macroeconomics. For example, on the microeconomic level, Boyd and Pang (2000), Ramanathan (2000), and Onut and Soner (2006) examined the energy efficiency of different sectors by using industry-level data. Similar studies include Azadeh et al. (2007), Wei et al. (2007), and Mukherjee (2008). At the macroeconomic level, Hu and Wang (2006) and Hu and Kao (2007) used DEA models to examine the total factor energy efficiency of various regions in the PRC and Japan, respectively. Yang and Shi (2008) compared traditional energy intensity indicators with a total factor energy efficiency indicator, and reported that DEA was better able to capture the effects of the resource endowments of regional economies on their energy efficiency. Yang et al. (2009) examined the influence of environmental factors on regional energy efficiency through an extended DEA model.

In the studies mentioned above, energy and non-energy inputs (e.g., capital and labor) were modeled to produce desirable or marketable outputs. However, energy consumption also results in undesirable by-products, i.e., emissions. Ignoring undesirable outputs might produce misleading results. Zhou and Ang (2008) evaluated the economy-wide energy efficiency of 21 member countries of the Organisation for Economic Co-operation and Development within a joint production framework that included both desirable and undesirable outputs.

However, in spite of widespread recognition that researchers should credit DMUs for their provision of desirable outputs, and penalize them for their provision of undesirable outputs, there has been no agreement on how to incorporate undesirable outputs into an efficiency model. Researchers generally model undesirable outputs in either of two ways. One is to treat undesirable variables as inputs. This approach is based on the economic argument that both inputs and undesirable outputs incur costs for a DMU, so DMUs usually want to reduce both as much as possible (e.g., Cropper and Oates 1992). That is to say, this approach assumes that undesirable outputs can be reduced at will by the management.⁶ An example of studies holding this view is Korhonen and Luptacik (2004). The other way is

⁶ Strong disposability of outputs implies that, given an input vector x , if an output vector y can be produced, then y^* can also be produced as long as $y^* \leq y$. Weak disposability of outputs means that if y can be produced, then θy ($0 \leq \theta \leq 1$) can also be produced proportionally (Fare et al. 1989).

Figure 1: DEA Model and Input Slack



Source: Hongliang Yang.

to model undesirable outputs as a single output and assume a weak disposability for them (e.g., Fare et al. 1989, 1996; Tyteca 1996, 1997). In the view of Fare and Grosskopf (2004), weak disposability generally indicates a Null-Joint relationship between desirable outputs and undesirable outputs in the production process.⁷ This means that undesirable outputs can only be reduced by decreasing overall production. These two ways have been critically debated in the academic journals (Hailu and Veeman 2001; Fare and Grosskopf 2003; Hailu 2003). Yang and Pollitt (2010) argue that various undesirable outputs often present quite different technical features, some of which may be weakly disposable and others strongly disposable. In efficiency analysis, there is a need to distinguish between weak and strong disposability among undesirable outputs. In the case of CO₂ emissions or any undesirable outputs with similar technical characteristics, assuming weak disposability is appropriate.

As shown above, lessons learned from earlier efficiency studies can provide us with clear and strong guidance when we evaluate economy-wide carbon performance.

Data Envelopment Analysis and Input Slack

Assume there are N regional economies (also N DMUs) using M non-energy inputs x and K energy inputs e to produce outputs y . Then let $X \in R_+^{M \times N}$ as the non-energy input matrix and $E \in R_+^{K \times N}$ as the energy input matrix, consisting of non-negative elements. Figure 1 illustrates the production processes of four DMUs: A , B , C , and D . The horizontal and vertical axes represent, respectively, non-energy and energy inputs used to produce one unit of desirable output. The DEA frontier is the piecewise linear convex hull $I-I'$. C and D operate on the efficiency frontier, representing the best economic-environmental performance given their respective resource endowments. A and B operate inefficiently and are therefore outside frontier $I-I'$.

We can calculate the efficiency of a DMU by comparing its distance relative to the best practice frontier. For DMU A , point A' is its improvement target on the frontier. To better its performance, A has to move to point A' by radially adjusting the level of its inputs, which is equal to $(1-\theta)x$. Here,

⁷ In terms of Fare and Grosskopf (2004), we can say that the desirable output vector y^d is Null-Joint with the undesirable outputs y^u if $(y^u, y^d) \in \text{output set } P(x)$ and $y^u = 0$, then $y^d = 0$. That is, if (y^u, y^d) is feasible and there are no undesirable outputs produced, then under null jointness, no desirable outputs can be produced.

θ is a dimensionless scalar and lies in the interval $(0, 1]$. The situation is different regarding B' as the improvement target of B , as we can reduce the level of inputs represented by the line segment $B'C$ but still produce the same output. This is called "input slack" (or "output surplus" for output) in the efficiency analysis literature. If we want to measure the efficiency of a DMU, we need to take both "radial adjustment" and "input slack" into account. These concepts form the theoretical foundation of modern efficiency analysis, and also of this paper.

Previous studies on economy-wide energy efficiency have confirmed the existence of energy input slacks in the PRC and in Japan (Hu and Wang 2006; Hu and Honma 2008; Yang and Shi 2008). As carbon emissions are closely linked to energy use, it is appropriate to hypothesize that the surplus of carbon emissions also exists due to energy input slacks. This will be carefully examined later.

DEA-Based Model for Economic–Energy–Environment Performance

Assume that vectors y^d and y^u refer to the desirable and undesirable outputs, respectively. Let $Y \in R_+$ be the output matrix, consisting of non-negative elements. Then the output matrix Y can be decomposed as

$$Y = \begin{pmatrix} Y^d \\ Y^u \end{pmatrix},$$

where a $P \times N$ matrix Y^d stands for desirable outputs and an $S \times N$ matrix Y^u stands for undesirable outputs. Then, the technology for this joint production process can be described:

$$T = \{(x, e, y^d, y^u) : (x, e) \text{ can produce } (y^d, y^u)\}.$$

Here, T is a closed and bounded set, allowing for the fact that a finite level of inputs can only produce a finite level of outputs (Fare and Primont 1995).

We assume that, given a certain level of desirable outputs, we would want to reduce the inputs and the undesirable outputs as much as possible. Based on the assumption of constant return to scale, for any economy $j(j = 1, \dots, N)$, we can formulate an input-oriented DEA model to depict its economic–environmental performance:

$$\begin{aligned} F_j(X, E, Y^d, Y^u) = \text{Min } \theta \\ \text{s.t. } Y^d \lambda \geq y_j^d \\ Y^u \lambda = \theta y_j^u \\ E \lambda \leq \theta e_j \\ X \lambda \leq \theta x_j \\ \lambda \in R_+ \end{aligned} \quad (1)$$

where λ is an $(N \times 1)$ vector of coefficients representing the intensity levels of DMUs in the construction of the reference efficiency frontier. Here, θ provides a standardized measurement for the economic–environmental performance of the regional economy j .

It is worth noting the model's mechanism for gauging the effects of the energy mix on carbon emissions. Zhou and Ang (2008) formulated a separate constraint for every energy source to capture the effects of changes in the energy mix. However, due to the nature of DEA modeling, for any fixed sample size, increasing the number of variables results in higher efficiency scores and a larger number of efficient DMUs. Therefore, this setting may reduce the discriminating power of the DEA model (Yang and Pollitt 2009). This paper adopts a different approach. First, following Hu and Wang (2006) and Yang and Shi (2008), the constraint for energy input is set up as:

$$E \lambda \leq \theta e_j \quad (2)$$

Here, all kinds of energy sources consumed by an economy $j(j = 1, \dots, N)$ are converted into the same thermal unit. Second, for undesirable outputs, the constraint is set up as

$$Y^u \lambda = \theta y_j^u \quad (3)$$

In the case of CO_2 , the total amount of emissions is calculated based on the amount of different fossil energy sources consumed. Because different fossil energy sources have different carbon emission factors, and non-fossil energy produces no carbon emissions, the combination of constraints (2) and (3) actually implies that, given a certain level of desirable outputs, the less energy use the better, and the lower carbon emissions the better.

Carbon Efficiency

Let TC be the target level of carbon emissions and AC be the actual level of carbon emissions of an economy. Thus, we can define an economy's carbon efficiency (CE) as

$$CE = \frac{TC}{AC} \quad (4)$$

As TC is always not larger than AC , an economy's carbon efficiency must be a value bounded between zero and one (i.e., $CE \in (0, 1]$).

Based on this definition, three kinds of analyses are possible. First, we can compare an economy's carbon efficiency with its carbon intensity. This would help us measure the effects of the economy's resource endowments on its carbon performance. Second, we can examine whether the country or region in question has a carbon emissions surplus. This would help us find the economy's carbon reduction potential. Third, we can analyze the relationship between carbon efficiency and economic growth, e.g., the relationship between an economy's energy efficiency and its GDP per capita. This would help us understand the effect of economic development on the economy's carbon performance.

Carbon Reduction Potential

We understand from the above analysis that, to produce a given level of desirable outputs, a carbon-efficient economy consumes the minimum level of energy and non-energy inputs and emits the minimum level of CO_2 . For an economy to be carbon efficient, it must operate at the carbon efficient frontier, and its target level of carbon emissions must be equal to its actual level of carbon emissions (i.e., $TC = AC$). Then the value of its carbon efficiency is unity (one). Conversely, if the actual level of carbon emissions of an economy is far away from the carbon-efficient frontier (i.e., $TC \ll AC$), then the value of its carbon efficiency approaches zero. This implies a carbon inefficient economy.

Thus, we can define an economy's carbon reduction potential as the difference between its actual carbon emissions status and its target carbon emissions status. It can be a relative ratio, such as

$$\begin{aligned} CRP &= 1 - CE \\ &= \frac{AC - TC}{AC} \quad (5) \end{aligned}$$

Clearly, an economy's carbon reduction potential can also be transformed into a figure using the format of carbon intensity.

Modified Carbon Intensity (MCI)

The carbon intensity of an economy j has traditionally been calculated using the following formula:

$$CI_j = \frac{AC_j}{GDP_j} \quad (6)$$

As mentioned above, the carbon efficiency of an economy lies in the interval $(0, 1]$. In order to facilitate the comparison between the newly defined carbon efficiency indicator and the traditional carbon intensity indicator, we can apply a modified carbon intensity indicator to economy j by using the following formula:

$$MCI_j = \frac{\min_{i=1}^N CI_i}{CI_j} \quad (7)$$

The modified carbon intensity indicator of any economy j is a value in the interval $(0, 1]$. Because it is a simple ratio between an economy's actual carbon intensity (i.e., CI_j) and the smallest carbon intensity in the sample (i.e., $\min_{i=1}^N CI_i$), it signifies the same thing as the traditional carbon intensity indicator. However, in contrast to the traditional carbon intensity indicator, the larger the modified carbon intensity of an economy, the better its carbon performance.

Research Data

This paper uses a research sample covering 29 provinces, autonomous regions, and municipalities in the PRC in 2005. All data are derived from the *China Statistics Yearbook* (various years) and from the *China Energy Statistics Yearbook* (2006).

This paper posits the provincial, regional, or municipal gross domestic product (GDP) as the desirable output, measured in billions of yuan (CNY). And it posits the labor force and capital stock as two non-energy inputs. The labor force is measured in thousands of employees. Capital stock is measured in billions of CNY, which is calculated using the following formula:

$$t+1 \text{ year capital stock} = t \text{ year capital stock} * (1 - \text{depreciation rate}) + t \text{ year capital formation}$$

The initial capital stock for calculation is assumed to be 10% of capital formation in 1952, and capital stock in different years has been transformed into 1990 price using GDP deflators. Energy consumption data have been standardized, measured in millions of tons of coal equivalent. Four categories of energy are considered: coal, oil, natural gas, and non-fossil energy. Given the focus of this paper, the model designates only CO₂ emissions as the undesirable output, measured in millions of tons. Carbon emissions factors for different fossil energy sources were taken from a report by the Energy Research Institute (ERI), the National Development and Reform Commission.⁸ Table 1 presents descriptive statistics for all these variables.

Table 1: Descriptive Statistics of Provinces, Autonomous Regions, and Municipalities

Variable	Unit	Mean	Maximum	Minimum	Std. Err.
GDP	10 ⁹ CNY ^a	6,812.3	22,366.5	543.3	5,520.0
GDP per capita	10 ³ CNY ^a	16.6	51.5	5.3	11.1
Labor	10 ³ ^b	2,340.9	6,324.3	267.6	1,654.3
Capital stock	10 ⁹ 1990 CNY ^a	30,247.9	87,987.9	3,633.7	23,082.5
Energy consumption	mtce ^c	90.5	236.1	8.2	57.4
CO ₂ emissions	10 ⁶ mt ^d	172.6	539.5	12.8	121.6

CO₂ = carbon dioxide, CNY = yuan, GDP = gross domestic product, Std. Err. = standard error.

^a Billions of yuan in 2005.

^b Thousands of employees.

^c Millions of tons of coal equivalent.

^d Millions of tons.

Source: China Statistics Yearbook, various years and *China Energy Statistics Yearbook* 2006.

⁸ Carbon emission factors for coal, oil, and natural gas are 0.732 t C/tce, 0.565 t C/tce, and 0.445 t C/tce, respectively.

Empirical Study and Results

Carbon Efficiency

Carbon efficiency and modified carbon intensity indicators were calculated for the sample provinces, autonomous regions, and municipalities, and the results are summarized in Table 2, which also lists the carbon performance rankings of all sample provinces (and autonomous regions, and municipalities) in terms of carbon efficiency and modified carbon intensity.

The results show that, in terms of the modified carbon intensity indicator, the average carbon performance was only 0.484 for all areas in the sample (i.e., all provinces, autonomous regions, and municipalities). In terms of the carbon efficiency indicator, the average carbon performance of all sample areas was 0.652. This indicates that an area's carbon performance is affected by its resource endowments (capital stock, energy use, energy mix, and labor force). In order to examine whether the differences between the two series of carbon performance scores are significant, a Wilcoxon-Mann-Whitney test⁹ was conducted. The test score was -2.637 , supporting the null hypothesis that the two series of carbon performance scores can be rejected at the significance level of 1%. This test demonstrated that the differences between the two series of scores were significant. In other words, incorporating resource endowment factors does make a difference in the final carbon performance evaluation.

The differences between the modified carbon intensity indicator and the carbon efficiency indicator are also apparent in their rankings of the sample areas. According to the modified carbon intensity indicator, Beijing took the lead in carbon performance. In contrast, according to the carbon efficiency indicator, Beijing, Shanghai, Guangdong, and Heilongjiang were all at the performance frontier.

It is worth stressing that carbon efficiency is a relative indicator. When a province, autonomous region, or municipality achieves a value of unity, that does not imply that its carbon performance has reached the extreme of carbon efficiency without any room for improvement. It just indicates that the area is taking the lead in carbon performance at the time of data collection. As technologies develop, particularly those related to energy usage and carbon reduction, an area currently operating on the frontier will very likely still have room to improve its carbon performance.

Carbon Reduction Potential

The sample areas' carbon intensity targets and carbon reduction potential were calculated under the carbon efficiency model, and Table 3 summarizes the results. The target carbon intensity of the sample areas in 2005 averaged 0.216 kilogram (kg) of CO₂/CNY, compared with the average

⁹ The Wilcoxon-Mann-Whitney test is a nonparametric statistic. Since the theoretical distribution of the efficiency score in DEA is usually unknown, the use of the parametric approach in this context is more susceptible. Please see Brockett and Golany (1996) and Cooper et al. (2000) for details.

Table 2: Carbon Performance of Sample Provinces in the PRC in 2005

No.	Provinces	Modified Carbon Intensity		Carbon Efficiency	
		Value	Ranking	Value	Ranking
1	Beijing	1.000	1	1	1
2	Tianjin	0.574	11	0.704	14
3	Hebei	0.358	21	0.779	10
4	Shanxi	0.119	29	0.255	27
5	Inner Mongolia	0.194	26	0.232	28
6	Liaoning	0.360	19	0.398	24
7	Jilin	0.329	22	0.348	26
8	Heilongjiang	0.321	23	1	1
9	Shanghai	0.766	6	1	1
10	Jiangsu	0.672	7	0.696	15
11	Zhejiang	0.792	4	0.835	6
12	Anhui	0.442	14	0.702	16
13	Fujian	0.779	5	0.822	8
14	Jiangxi	0.602	9	0.636	19
15	Shandong	0.394	15	0.426	23
16	Henan	0.393	16	0.746	12
17	Hubei	0.457	13	0.765	11
18	Hunan	0.483	12	0.834	7
19	Guangdong	0.948	2	1	1
20	Guangxi	0.647	8	0.793	9
21	Hainan	0.802	3	0.846	5
22	Sichuan (including Chongqing)	0.557	10	0.686	17
23	Guizhou	0.163	27	0.507	20
24	Yunnan	0.348	20	0.650	18
25	Shaanxi	0.384	18	0.507	21
26	Gansu	0.315	25	0.724	13
27	Qinghai	0.384	17	0.493	22
28	Ningxia	0.128	28	0.172	29
29	Xinjiang	0.321	24	0.359	25
Average		0.484		0.652	

PRC = People's Republic of China.

Source: Hongliang Yang.

actual carbon intensity of 0.40 kg. Thus, the carbon intensity reduction potential was about 35%.

Because the carbon efficiency scores were based on performance on the domestic frontier, the PRC could achieve this amount of carbon reduction by using domestically available techniques. These include carbon-efficient technologies and modern economic management approaches. From another perspective, the results demonstrate the importance at this stage of disseminating climate change-

related technology and management approaches across the PRC.

Achieving this reduction will not be easy, however. In November 2009, the government announced its intention of reducing the PRC's carbon intensity to 40%–45% by 2020, compared with the level in 2005. Table 3 suggests that, even if the national average of carbon efficiency in 2020 could match that of the frontier areas (e.g., Beijing and Shanghai) in 2005, it would mean a reduction

Table 3: Actual and Target Carbon Intensity and Reduction Potential

No.	Provinces	Actual CO ₂ /GDP (kg/CNY)	11th Five-Year Plan EE Target (%)	Target CO ₂ /GDP (kg/CNY)	CO ₂ /GDP Reduction Potential (%)
1	Beijing	0.143	20	0.143	0
2	Tianjin	0.264	20	0.186	30
3	Hebei	0.423	20	0.329	22
4	Shanxi	1.202	25	0.307	74
5	Inner Mongolia	0.738	25	0.171	77
6	Liaoning	0.399	20	0.159	60
7	Jilin	0.436	30	0.152	65
8	Heilongjiang	0.446	20	0.446	0
9	Shanghai	0.187	20	0.187	0
10	Jiangsu	0.213	20	0.149	30
11	Zhejiang	0.181	20	0.151	16
12	Anhui	0.324	20	0.228	30
13	Fujian	0.184	16	0.151	18
14	Jiangxi	0.238	20	0.151	36
15	Shandong	0.364	22	0.155	57
16	Henan	0.365	20	0.272	25
17	Hubei	0.314	20	0.240	23
18	Hunan	0.297	20	0.248	17
19	Guangdong	0.151	16	0.151	0
20	Guangxi	0.222	15	0.176	21
21	Hainan	0.179	12	0.151	15
22	Sichuan (including Chongqing)	0.258	20	0.177	31
23	Guizhou	0.880	20	0.446	49
24	Yunnan	0.412	17	0.268	35
25	Shaanxi	0.374	20	0.190	49
26	Gansu	0.455	20	0.330	28
27	Qinghai	0.374	17	0.184	51
28	Ningxia	1.123	20	0.194	83
29	Xinjiang	0.447	20	0.160	64
	Average	0.400		0.216	35

CNY = yuan, CO₂ = carbon dioxide, EE = energy efficiency, GDP = gross domestic product, kg = kilogram.

Source: Hongliang Yang.

of carbon emissions of only about one-third. As shown in Table 1, there is a huge imbalance in economic development between the modern and lagging areas in the PRC. In 2005, the largest gap amounted to a ratio of about 10:1 in the sizes of GDPs per capita. Therefore, achieving this 40%–45% reduction target will require more inputs than the traditional carbon intensity indicator implies.

Carbon Efficiency and Economic Development

To determine the relationship between regional carbon efficiency and economic development, this paper categorizes 29 areas into three groups according to their geographic locations: east, central, and west. The eastern region includes

Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The central region includes Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, and Guangxi. The western region includes Sichuan (plus Chongqing), Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. Table 4 summarizes the results for the three regions regarding the modified carbon intensity and carbon efficiency indicators.

The results show that in 2005, the eastern region took the lead in carbon performance, the central came second, and the west lagged behind, according to both the modified carbon intensity and carbon efficiency indicators. Given that the eastern, central, and western regions also rank first, second, and third, respectively, in terms of GDP per capita

Table 4: Carbon Performance of Different Regions

No.	Regions	Modified Carbon Intensity	Carbon Efficiency
1	East	0.667	0.773
2	Central	0.399	0.631
3	West	0.325	0.512

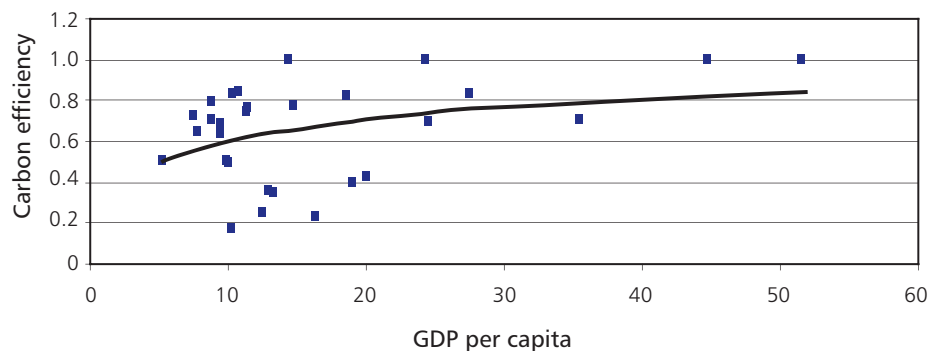
Source: Hongliang Yang.

and other economic development factors, the results in Table 4 imply that a region's carbon performance may be positively related to its economic development. Figure 2 plots the carbon efficiency scores versus GDP per capita of the sample areas.

Figure 2 illustrates the general relationship between an area's carbon efficiency and its GDP per capita. The carbon efficiency scores were then linearly regressed on the GDP per capita of sample areas to examine that relationship. Because the carbon efficiency scores lie in the interval (0,1], to avoid any misspecification of the linear regression, a Tobit regression, was also conducted for cross-checking purpose. Table 5 shows the results of both regressions.

Table 5 shows some important findings. First, the signs of the estimated coefficients for GDP per capita are quite stable in both regressions. This confirms that there is a positive relationship between the two variables. Second, GDP per capita provides a relatively good explanation for the variation in the carbon efficiency scores. The hypothesis that GDP per capita has no influence on the carbon efficiency of a region can be rejected at a better than 5% significance level in both regressions. This actually confirms the impact of sample areas' GDP per capita on their carbon efficiency.

Figure 2: Carbon Efficiency and Gross Domestic Product Per Capita



Source: Hongliang Yang.

Table 5: Regression Results of Carbon Efficiency versus GDP Per Capita

Carbon Efficiency	Linear Regression			Tobit Regression		
	Coefficient	Standard Error	$P > t $	Coefficient	Standard Error	$P > t $
Constant	0.5042	0.0752	0.000	0.4527	0.0884	0.000
GDP per capita	0.0089	0.0038	0.026	0.0135	0.0049	0.011

GDP = gross domestic product.

Source: Hongliang Yang.

Conclusions and Policy Suggestions

The traditional carbon intensity indicator is too simple to capture the multidimensional features of the development of an economy. This paper suggests that we consider economy-wide carbon performance from a total factor perspective. Based on the lessons learned from the efficiency analysis literature, this paper proposed a new approach: measuring the carbon performance of an economy by using a total factor DEA-based model. This paper then presented an empirical study using data collected from PRC provinces, autonomous regions, and municipalities in 2005.

The major contributions of this paper are as follows: First, to better elaborate the mechanism of economy-wide carbon performance, and to avoid any unnecessary confusion with the existing literature, this paper defined a new concept—carbon efficiency, as the ratio of an economy's target CO₂ emissions and its actual CO₂ emissions. It calculated the carbon efficiency in 2005 of 29 provinces, autonomous regions, and municipalities in the PRC. The results show that an area's carbon performance can be significantly different from what the traditional carbon intensity indicator would suggest. This implies that an economy's carbon performance is affected by its resource endowments, i.e., capital stock, energy supply mix, energy consumption, labor force, and others. Therefore, policy makers will not achieve an adequate reduction of carbon emissions if they fail to take resource endowments into account.

Second, this paper presented calculations of carbon reduction potential that used the DEA-based model. The results show that, if all sample areas could operate at the 2005 efficiency frontier, they could generate the same GDP while avoiding roughly one-third of their actual CO₂ emissions. Because the benchmark for calculating carbon efficiency is the domestic efficiency frontier, the PRC could achieve this reduction by using domestically available technologies and management methods. This means that it is important to disseminate climate change-related technologies and management methods across the PRC. The policy implications may be important not only for the PRC, but also for other developed and developing countries.

Third, this paper explored the relationship between an economy's carbon efficiency and its level of development. The results confirm that they are closely linked. We should not talk about an economy's carbon performance as if it were a purely technical issue, without viewing it within the broader context of economic development. This paper's findings conform with the Copenhagen Accord, which states that "...social and economic development and poverty eradication are the first and overriding priorities of developing countries and that a low-emission development strategy is indispensable to sustainable development" (para. 2, Copenhagen Accord 2009).

Fourth, this paper found that the PRC's recently announced carbon reduction target—a 40%–45% drop in carbon intensity from 2005 level by 2020—will not be easy to achieve.

The results suggest that, even if the national average of carbon efficiency in 2020 matched the frontier-level of 2005, the result would be a reduction of carbon intensity of only about one-third. Considering the huge development gap between the eastern and western regions in the PRC, achieving this 40%–45% reduction will require more investment in carbon-efficient technologies and more improvements in economic management.

An economy's carbon efficiency is not only closely linked to that economy's level of development but also to its international competitiveness and energy

security. As the world pays more attention to climate change, there must be more studies on this issue. This paper will hopefully help attract more attention to total factor carbon efficiency studies. Future research could focus on two questions. First, if the dissemination of internationally available most-efficient technologies is possible, then what is the estimated carbon reduction potential going to be? Second, would a narrowing of regional imbalances in GDPs per capita result in a higher overall carbon efficiency? The answers to both questions are expected to have very meaningful policy implications at both the national and international levels.

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Carbon Efficiency, Carbon Reduction Potential, and Economic Development in the People's Republic of China: A Total Factor Production Model

"Carbon intensity" is the traditional measure of an economy's carbon performance. However, it is incapable of capturing the multidimensional features of an economy's carbon performance, particularly when increased emissions have causes other than poor emitting technology, such as changes in the energy mix or the substitution of energy for labor. Hence, it can sometimes be a poor yardstick for comparing countries with different natural resources or factors of production. Introducing the concept of "carbon efficiency," based on Data Envelopment Analysis, this study calculates the carbon performance in 2005 of 29 regions in the People's Republic of China with results different from what the carbon intensity indicator would have suggested: Better carbon performance is associated with higher levels of economic development and greater resource endowments.

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