# Carbon Emission Performance Evaluation and Allocation in Chinese Cities

**Abstract**: This paper presents a DEA approach with multiple abatement factors to evaluate $CO_2$ emission performance and allocate $CO_2$ emission quotas in Chinese cities. We first consider the difference of marginal abatement costs among cities, and construct the non-radial directional distance function with multiple abatement factors. The total-factor $CO_2$ emission performance index and its dynamic change index are then proposed to measure $CO_2$ emission performance. Considering equity and efficiency, we develop a composite index by the hybrid method to allocate emissions quota, which considers $CO_2$ emissions as well as $CO_2$ emission performance. Then we conduct an empirical study using inputs and outputs dataset of 71 Chinese cities in 2005-2012. Chinese cities have poor energy efficiency and still have high $CO_2$ emissions. The eastern region outperforms the central region and the western region performs worst, whereas the dynamic $CO_2$ emission performance of the central region has the largest increase. The change of $CO_2$ emission performance is driven mainly by technological advances. As for the $CO_2$ emission allocation, the composite index method encourages cities to reduce emissions and enhance emission performance through carbon trading market. It also motivates cities with high historical emissions to reduce their emissions by improving technology when they have poor $CO_2$ emission performance.

**Keywords**: data envelopment analysis; total-factor $CO_2$ emission performance; $CO_2$ emission allocation; multiple abatement factors; urban environment

## 1. Introduction

China has been the largest $CO_2$ emitter in the world since 2008 (BP, 2013). Auffhammer and Carson (2008) pointed out that there would be a sharply increase of China's $CO_2$ emissions per capita in the future, which would be far more than the emission quota of Kyoto agreement. It will certainly bring a lot of burden for China and even the world. As the biggest energy consumer and carbon emitter, China is under great pressure to reduce carbon emissions. In 2009 Copenhagen Climate Change Conference, Chinese government committed mandatory goal of a 40-45%

R3.4

R2.1/3.4

decrease in carbon intensity by 2020 compared to the 2005 level. In 2015 Paris Climate Change Conference, this goal was committed to be dropped by 60-65% in 2030 compared to the 2005 level. Chinese government need to allocate the national carbon reduction targets among regions in order to achieve the total targets successfully.

Given the diversity of economic and social development among different regions in China, regions' reduction capacity and potential are also different. China is in a period of rapid urbanization, which has led to increased demands for energy (Wang et al., 2013). Approximately 85% of China's $CO_2$ emissions are related to urban energy consumption (Mi et al., 2016). Therefore, there is an urgent need to allocate emission quotas among cities, as such work is fundamental to achieve national reduction goals. It helps us to undertake "common but differentiated reduction responsibilities", so as to promote urban green transformation.

In literature, emission quota allocation principles can be mainly divided into two R1.1/3.2
categories, namely fairness and efficiency principle (Rose, 1990; Zhou and Wang, 2016; Zhou et al., 2017). Under the two principles, many different methods have been R1.1/3.2
proposed for emission quota allocation. Indicator method based on the fairness principle is the most commonly approach. It consists of single and composite indicator approaches. Single indicator like the cumulative emissions per capita, GDP and population (e.g., Ding et al., 2009; Zhou et al., 2013; Wei et al., 2014) are selected as the allocation indicator based on fairness principle. Composite indicator approach (e.g., Hatefi and Torabi, 2010; Yi et al.,2011; Luzzati and Gucciardi, 2015) has received growing attention recently as it can integrate different fairness criteria. Meanwhile, the optimization method, especially DEA model, has been explored for emission quota allocation based on the efficiency principle. The ZSG-DEA model was employed by Wang et al. (2013) and Miao et al. (2016) to allocate $CO_2$ emissions in China. Wei et al. (2012) used a slacks-based DEA model to allocate $CO_2$ abatement among provinces in China. In addition, game theoretic method has been advocated to search for the optimal allocation of emission permits (e.g., Mackenzie et al., 2008; Liao et al., 2015). Some approaches that uses multiple indicators without constructing a composite indicator (e.g., den Elzen, 2008; Ekholm et al., 2010) or incorporate multiple groups of the above methods (e.g., Yu et al., 2014; Zhang et al., 2014) can be divided into the hybrid method. It can consider different fairness and efficiency principle simultaneously.

On the one hand, fairness principle is often linked to more general concepts of distributive justice (Rose, 1990). The fairness principle ensures emitters to undertake reduction burden justly. On the other hand, allocation methods under the efficiency principle may not only take regional economic development into consideration, but also the regional mitigation potential. Although few research (Wei et al.,2013; Zhang and Hao, 2016; Yang et al., 2017) proposed allocation methods based on equity and efficiency principle, it should be noted that the majority literature rarely consider fairness and efficiency principle simultaneously, especially taking the emission performance as efficiency principle. It is significant for regional emission quota allocation as it not only take regional equity into consideration, but also the efficiency to achieve the total reduction goal, while at the same time emphasizing regional development conditions.

As for the efficiency principle, $CO_2$ emission performance reflects the emission efficiency, which can be used as the allocation method based on the efficiency principle. Previous studies are likely to use single indicator (e.g., carbon emission intensity, $CO_2$ emissions per unit output) to assess the $CO_2$ emission performance (e.g., Ang and Choi, 2002; Sun, 2005; Tol et al., 2009). It only reflects a part of $CO_2$ emission performance, while $CO_2$ emission performance is the result of energy R3.4 consumption and economic development (Ramanathan, 2009). Zhou et al. (2010) proposed the concept of total-factor carbon emission performance with DEA model, which reflects the dynamic change of total-factor carbon emission performance. It is later employed and extended by many studies. Examples of such studies include Zhou et al. (2012), Wang et al. (2013), Zhang and Choi (2013). Recently, allowing the incorporation of group heterogeneity and non-radial slack, Zhang and Choi (2013) constructed the metafrontier non-radial Malmquist $CO_2$ emission performance index to measure change of total-factor $CO_2$ emission performance. Nabavieh et al. (2015) assessed the carbon emission performance of Iran fossil fuel power plants with this method. Zhang et al. (2015) developed a bootstrapped non-radial Malmquist index to analyze Chinese transportation industry's carbon emission performance. Duan et al. (2016) used the bootstrapped directional distance function approach to evaluate energy and $CO_2$ emission performance of China's thermal power industry. Nevertheless, the previous studies analyze total-factor $CO_2$ emission performance are R3.4 satisfied with the Shephard production technology. The Shephard production technology uses a single abatement factor. It is proved that single abatement factor is insufficient to correctly represent a convex technology exhibiting weak disposability of undesirable and desirable outputs (Kuosmanen and Podinovski, 2009). Meanwhile, DMUs have different marginal abatement costs. Using a single abatement factor does not satisfy environmental economics theory. It can not reflect the differences among production units correctly (Kuosmanen, 2005).

With regard to $CO_2$ emission performance, studies mainly focus on the $CO_2$ emission performance of China at the national or provincial level (Guo et al., 2011; Wei et al., 2012; Song et al., 2013), industry level (Lee and Zhang, 2012; Chang et al., 2013; Zhou et al., 2013) or plant level (Zhou et al., 2012; Zhou et al., 2014; Lin and Wang, 2015). Meanwhile, many scholars propose emission quota allocation from R1.1 multiple perspectives such as emission allocation among countries (e.g., Persson and Azar, 2006; Ding et al., 2009; Pan et al., 2014), decomposition of national emission quotas into provinces (e.g., Wei et al., 2012; Zhang et al., 2013; Yu and Wei, 2014; Zhang and Hao, 2015), and distribution of tradable $CO_2$ emission quota in carbon emission trading system (e.g., Bohringer and Lange, 2005; Neuhoff et al., 2012; Park et al., 2012). However, most literature rarely did research from urban perspective. China is in rapid urbanization process, which increases energy consumption and contributes heavily towards climate change. Cities are critical for fully realizing carbon reduction goals.

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Technically, we first construct the total-factor $CO_2$ emission performance index (TCPI) and non-radial global $CO_2$ emission performance dynamic change index (NGMCPI) with multiple abatement factors to estimate $CO_2$ emission performance and its dynamic change. Then we take historical cumulative $CO_2$ emissions and $CO_2$ emission performance index as outputs, and use Index DEA model to calculate the composite allocation index, which considers fairness and efficiency principle simultaneously. We apply the models to the urban dataset to evaluate Chinese urban $CO_2$ emission performance and $CO_2$ emission allocation. We compare our emission performance results with the result using single abatement factor production technology. Meanwhile, we compare our results with results under fairness principle and results under efficiency principle.

This paper differs from the previous studies in the following aspects. First, as R3.1 most studies related with emission quota allocation often only focus on the fairness or efficiency principle, we consider fairness and efficiency principle simultaneously and propose a composite index for emission quota allocation by combining historical cumulative $CO_2$ emissions and $CO_2$ emission performance. It not only take regional equity into consideration, but also the efficiency to achieve the total reduction goal, while at the same time emphasizing regional development conditions. Second, different from earlier studies using single abatement factor, we start from considering DMUs have different pollution treatment capacity, and define the total-factor $CO_2$ emission performance index (TCPI) and non-radial global $CO_2$ emission performance dynamic change index (NGMCPI) with multiple abatement factors to measure total-factor $CO_2$ emission performance and its dynamic change. Such production technology comply with environmental economics theory and meet the convexity assumptions. Third, while previous relevant studies mainly focus on the performance and allocation measurement at China's national/provincial level, this study does empirical research at urban level as a large amount of China's $CO_2$ emissions are related to urban energy consumption. There is an urgent need to evaluate $CO_2$ emission performance and allocate emission quotas among cities, as such work is fundamental to achieve national reduction goals.

The rest of this paper is organized as follows. In section 2, we first introduce the Kuosmanen production technology with multiple abatement factors. We then propose the non-radial global directional distance function and develop total-factor $CO_2$ emission performance index and its dynamic change index. The composite allocation indicator is also proposed. Section 3 presents an empirical study using the proposed approach to modeling the $CO_2$ emission performance and $CO_2$ emission allocation in Chinese cities. Section 4 concludes this study.

## 2. Methodology

### 2.1. Total-factor $CO_2$ emission performance index

In the use of DEA model to deal with $CO_2$ and other undesirable outputs, there are three main methods. The first method is to treat the undesirable outputs as inputs (Reinhard et al., 1999; Hailu and Veeman, 2001). But this method can not reflect the true production process and involve two problems. On the one hand, free disposability of inputs and undesirable outputs means a finite amount of inputs can produce infinite amount of undesirable outputs. It violates the law of mass conservation. On the other hand, free disposability assumption does not reflect the links between desirable and undesirable outputs, especially the weak disposability between desirable outputs and undesirable outputs. The second method is to make data transformation of undesirable outputs, and then use conventional efficiency evaluation model (Seiford and Zhu, 2002; Hua et al., 2007). However, this method adds a strong convexity constraint, which can only be solved under variable returns to scale condition. The third method is to introduce an abatement factor reflecting weak disposability between desirable and undesirable outputs, which is called Shephard production technology. Färe et al. (1986, 1989) proposed the concept of strong disposability and weak disposability, and defined production possibility sets respectively. Using DEA model with undesirable outputs to measure environment efficiency, weak disposability assumption is widely used (e.g., Yu, 2004; Zhou et al., 2010; Zhang and Choi, 2013; Lee, 2014). However, the production technology should satisfy the minimum extrapolation principle, model should be the smallest possible and does not contain any arbitrary activities (Banker et al.,1984). Shephard production technology using a single abatement factor is insufficient to correctly reflect convexity exhibiting weak disposability of desirable and undesirable outputs. It may lead to bias estimation of production efficiency (Kuosmanen and Podinovski, 2009). Kuosmanen (2005) considered multiple abatement factors and propose Kuosmanen production technology. It can effectively solve the above problems. Podinovski and Kuosmanen (2011) compared the production possibility set size of Shephard production technology and Kuosmanen production technology, it was verified that the Kuosmanen technology can meet the convexity assumptions. In this paper, we adopt the Kuosmanen technology to model undesirable outpus and construct the total-factor $CO_2$ emission performance index.

In order to illustrative Kuosmanen technology clearly, we start with the weak disposability, which use one single abatement factor. Suppose the production activity is characterized by $(X,Y,Z)$, where $X=(x_1,\cdots,x_N)\in R_+^N$ is the vectors of inputs, $Y=(y_1,\cdots,y_M)\in R_+^M$ is the vectors of desirable outputs and $Z=(z_1,\cdots,z_J)\in R_+^J$ is the vectors of undesirable outputs. We assume there are $K$ DMUs, and the observed activities are denoted by $(X^k,Y^k,Z^k), k=1,\cdots,K$. The production technology $T$ is said to be weak disposability if $(X,Y,Z)\in T$ and $\theta\in[0,1]$, $(X,\theta Y,\theta Z)\in T$. With weak disposability, reducing undesirable outputs has an impact on other normal outputs. We need to sacrifice the desirable outputs to reduce the undesirable outputs. It is consistent with the actual production activities. But the production technology uses a single abatement factor to reflect weak disposability between desirable outputs and undesirable outputs, which does not satisfy the convexity assumption (Kuosmanen and Podinovski, 2009). As DMUs (e.g., enterprises) have different pollution treatment capacity, it is cost effective for enterprises whose marginal abatement costs is low, while it is unfavorable for enterprises whose marginal abatement costs is high. Using a single abatement factor does not comply with environmental economics theory. Therefore, Kuosmanen (2005) propose a production technology with multiple abatement factors. It uses individual abatement factors $\theta^k$ attached to each observed activity $k = 1, \cdots, K$. The Kuosmanen technology is convex under the weak disposability of desirable and undesirable outputs. The production possibility set is as follows:

$$
\begin{aligned}
\hat{T}_K = \{(X, Y, Z):\ & \sum_{k=1}^{K} w^k x_n^k \le x_n, n = 1, \cdots, N \\
& \sum_{k=1}^{K} \theta^k w^k y_m^k \ge y_m, m = 1, \cdots, M \\
& \sum_{k=1}^{K} \theta^k w^k z_j^k = z_j, j = 1, \cdots, J \\
& \sum_{k=1}^{K} w^k = 1 \\
& w^k \ge 0, k = 1, \cdots, K \\
& 0 \le \theta^k \le 1, k = 1, \cdots, K\}.
\end{aligned} \tag{1}
$$

where variables $w = (w^1, \cdots, w^K)$ are referred to as the intensity weights.

We can use the formula for substitution: $\lambda^k = \theta^k w^k, \mu^k = (1-\theta^k) w^k, k = 1, \cdots, K$, so that $\lambda^k + \mu^k = w^k$. Thus, the formula (1) can be converted to:

$$
\begin{aligned}
\hat{T}_K = \{(X, Y, Z):\ & \sum_{k=1}^{K} (\lambda^k + \mu^k) x_n^k \le x_n, n = 1, \cdots, N \\
& \sum_{k=1}^{K} \lambda^k y_m^k \ge y_m, m = 1, \cdots, M \\
& \sum_{k=1}^{K} \lambda^k z_j^k = z_j, j = 1, \cdots, J \\
& \sum_{k=1}^{K} (\lambda^k + \mu^k) = 1 \\
& \lambda^k, \mu^k \ge 0, k = 1, \cdots, K\}.
\end{aligned} \tag{2}
$$

The directional distance function (DDF) based on the Kuosmanen technology proposed by Podinovski and Kuosmanen (2011) is radial. It means that the change ratio of undesirable outputs is the same as the ratio of desirable outputs. It may overestimate efficiency when there is some slack (Fukuyama and Weber, 2009). The non-radial method is often advocated to overcome this limitation (Chang and Hu, 2010; Zhang and Choi, 2013). Therefore, we propose the following non-radial directional distance function (NDDF) with Kuosmanen technology:

$$\vec{ND}\left(X^0, Y^0, Z^0; g^x, g^y, g^z\right) = \sup\left\{\omega\cdot\phi \middle| (x^0 - \omega^x\phi^x g^x, y^0 + \omega^y\phi^y g^y, z^0 - \omega^z\phi^z g^z) \in T\right\} \quad (3)$$

where $\omega^T = (\omega^x, \omega^y, \omega^z)^T$ denotes weight vector of inputs and outputs. $g^x, g^y, g^z$ are directional vector. $\phi = (\phi^x, \phi^y, \phi^z)^T \geq 0$ denotes a vector of scaling factors representing individual inefficiency measures for inputs and outputs. We can use the formula for substitution: $x_n = x_n^0 - \phi_n^x g_n^x$, $y_m = y_m^0 + \phi_m^y g_m^y$, $z_j = z_j^0 - \phi_j^z g_j^z$.

We can calculate the NDDF value for a specific DMU $k^0$, denoted as $\vec{ND}\left(X^0, Y^0, Z^0; g^x, g^y, g^z\right)$ by solving the following DEA model:

$$\begin{aligned}
\vec{ND}\left(X^0, Y^0, Z^0; g^x, g^y, g^z\right) = \max \sum_{n=1}^{N} \omega_n^x\phi_n^x + \sum_{m=1}^{M} \omega_m^y\phi_m^y + \sum_{j=1}^{J} \omega_j^z\phi_j^z \\
\text{s.t. } \sum_{k=1}^{K} (\lambda^k + \mu^k) x_n^k \leq x_n^o - \phi_n^x g_n^x, n = 1, \cdots, N \\
\sum_{k=1}^{K} \lambda^k y_m^k \geq y_m^o + \phi_m^y g_m^y, m = 1, \cdots M \\
\sum_{k=1}^{K} \lambda^k z_j^k = z_j^o - \phi_j^z g_j^z, j = 1, \cdots, J \\
\sum_{k=1}^{K} (\lambda^k + \mu^k) = 1 \\
\lambda^k, \mu^k \geq 0, k = 1, \cdots, K.
\end{aligned} \quad (4)$$

Suppose that each DMU uses capital (K), labor (L), energy (E) as inputs to generate the gross product (Y), a desirable output, and $CO_2$ emissions (C), an undesirable output. And we set the weight vector to (1/9, 1/9, 1/9, 1/3, 1/3) and the directional vectors to $g = (-K, -L, -E, Y, -C)$. We follow Zhou et al. (2012) and define the static total-factor $CO_2$ emission performance index (TCPI) as the ratio of potential target carbon intensity to actual carbon intensity. The TCPI is formulated as follows:

$$TCPI = \frac{(Z - \phi^{z*}Z)/(Y + \phi^{y*}Y)}{Z/Y} = \frac{1 - \phi^{z*}}{1 + \phi^{y*}} \quad (5)$$

TCPI seeks to measure the maximal possible reduction of carbon intensity, which can be used to measure the carbon emission performance. The higher value of TCPI, the better is the carbon emission performance. When calculating the dynamic changes of carbon emission performance, conventional Malmquist index are defined as geometric mean of the directional distance functions of two consecutive periods. To measure environmentally sensitive productivity growth, Chung et al. (1997) proposed Malmquist-Luenberger productivity index (ML index). However, as the new frontier has shifted, the cross-periods DDFs are not free from the infeasibility problem in LP calculation, and the observed DMU may not be included in the production frontier. Moreover, the Malmquist index calculated by geometric mean does not have features of circularity and transitivity. To solve these problems, Pastor and Lovell (2005) developed the global Malmquist index. Then Oh (2010) applied it to the ML index and proposed the global Malmquist-Luenberger index.

Two production technologies are defined: the contemporaneous and global production technologies. The contemporaneous production technology is defined as $T^C = \{(X^t, Y^t, Z^t) : X^t \text{ can produce } (Y^t, Z^t)\}$ where $t = 1, \cdots, T$. This frontier represents the production technology described in equation (2) for a special $t$ only. Then we define the global production technology as $T^G = T^1 \cup T^2 \cup \cdots \cup T^T$. This frontier consists of a single technology constructed from observations spanning the whole period for all observations. The global production technology thus envelops all contemporaneous production technologies, and we assume that all DMUs are able to access this global technology through innovation activities. We can express the directional distance function based on these two production technologies.

We define $C$ as the contemporaneous production technology and the contemporaneous directional distance function based on the contemporaneous production technology is as follows, we replace $\vec{ND}^C(X^0, Y^0, Z^0; g^x, g^y, g^z)$ with $\vec{ND}^C(.)$ to save space:

$$\vec{ND}^C(.) = \sup\left\{\omega \cdot \phi^C \middle| (x^0 - \omega^x \phi^{C,x} g^x, y^0 + \omega^y \phi^{C,y} g^y, z^0 - \omega^z \phi^{C,z} g^z) \in T^C\right\} \tag{6}$$

And we define $G$ as the global production technology and the global directional distance function based on the global production technology is as follows:

$$\vec{ND}^G(.) = \sup\left\{\omega \cdot \phi^G \middle| (x^0 - \omega^x \phi^{G,x} g^x, y^0 + \omega^y \phi^{G,y} g^y, z^0 - \omega^z \phi^{G,z} g^z) \in T^G\right\} \tag{7}$$

To calculate and decompose the non-radial global total-factor $CO_2$ emission performance index (NGMCPI), we need to solve four different directional distance functions: $\vec{ND}^{C}(.t)$, $\vec{ND}^{C}(.t+1)$, $\vec{ND}^{G}(.t)$ and $\vec{ND}^{G}(.t+1)$. Based on equation (4), we can solve the contemporaneous directional distance functions $\vec{ND}^{C}(.t)$ and $\vec{ND}^{G}(.t+1)$ for each period. The global directional distance functions $\vec{ND}^{G}(.t)$ and $\vec{ND}^{G}(.t+1)$ can be solved through the following DEA model (8) and (9):

$$\begin{aligned}\vec{ND}^{G}\left(X^{0},Y^{0},Z^{0};g^{x},g^{y},g^{z}\right)=\max \sum_{n=1}^{N}\omega_n^x\phi_n^{G,x}+\sum_{m=1}^{M}\omega_m^y\phi_m^{G,y}+\sum_{j=1}^{J}\omega_j^z\phi_j^{G,z}\\
\text{s.t. } \sum_{s=1}^{T}\sum_{k=1}^{K}(\lambda^{k,t}+\mu^{k,t})x_n^{k,t}\le x_n^o-\phi_n^{G,x}g_n^x,\ n=1,\cdots,N\\
\sum_{s=1}^{T}\sum_{k=1}^{K}\lambda^{k,t}y_m^{k,t}\ge y_m^o+\phi_m^{G,y}g_m^y,\ m=1,\cdots M\\
\sum_{s=1}^{T}\sum_{k=1}^{K}\lambda^{k,t}z_j^{k,t}=z_j^o-\phi_j^{G,z}g_j^z,\ j=1,\cdots,J\\
\sum_{s=1}^{T}\sum_{k=1}^{K}(\lambda^{k,t}+\mu^{k,t})=1\\
\lambda^{k,t},\mu^{k,t}\ge 0,\ k=1,\cdots,K.\end{aligned} \tag{8}$$

$$\begin{aligned}\vec{ND}^{G}\left(X^{0},Y^{0},Z^{0};g^{x},g^{y},g^{z}\right)=\max \sum_{n=1}^{N}\omega_n^x\phi_n^{G,x}+\sum_{m=1}^{M}\omega_m^y\phi_m^{G,y}+\sum_{j=1}^{J}\omega_j^z\phi_j^{G,z}\\
\text{s.t. } \sum_{s=1}^{T}\sum_{k=1}^{K}(\lambda^{k,t+1}+\mu^{k,t+1})x_n^{k,t+1}\le x_n^o-\phi_n^{G,x}g_n^x,\ n=1,\cdots,N\\
\sum_{s=1}^{T}\sum_{k=1}^{K}\lambda^{k,t+1}y_m^{k,t+1}\ge y_m^o+\phi_m^{G,y}g_m^y,\ m=1,\cdots M\\
\sum_{s=1}^{T}\sum_{k=1}^{K}\lambda^{k,t+1}z_j^{k,t+1}=z_j^o-\phi_j^{G,z}g_j^z,\ j=1,\cdots,J\\
\sum_{s=1}^{T}\sum_{k=1}^{K}(\lambda^{k,t+1}+\mu^{k,t+1})=1\\
\lambda^{k,t+1},\mu^{k,t+1}\ge 0,\ k=1,\cdots,K.\end{aligned} \tag{9}$$

The weight vectors and directional vectors are the same as in equation (4). $(x_n^{k,t},y_m^{k,t},z_j^{k,t})$ and $(x_n^{k,t+1},y_m^{k,t+1},z_j^{k,t+1})$ means input n, desirable output m and undesirable output j of DMU k at period t and t+1, respectively. $(\lambda^{k,t},\mu^{k,t})$ and $(\lambda^{k,t+1},\mu^{k,t+1})$ means $\lambda$ and $\mu$ of DMU k at period t and t+1, respectively. Based on these values for different directional distance functions, we have the four corresponding TCPI values as follows:

$$TCPI^{C}\left(\overset{t}{.}\right)=\left[\frac{(Z-\phi_z^{C*}Z)/(Y+\phi_y^{C*}Y)}{Z/Y}\right]^{t}=\left(\frac{1-\phi_z^{C*}}{1+\phi_y^{C*}}\right)^{t} \tag{10}$$

$$\mathrm{TCPI}^{C}\left(.^{t+1}\right)=\left[\frac{(Z-\phi_z^{C*}Z)/(Y+\phi_y^{C*}Y)}{Z/Y}\right]^{t+1}=\left(\frac{1-\phi_z^{C*}}{1+\phi_y^{C*}}\right)^{t+1} \tag{11}$$

$$\mathrm{TCPI}^{G}\left(.^{t}\right)=\left[\frac{(Z-\phi_z^{G*}Z)/(Y+\phi_y^{G*}Y)}{Z/Y}\right]^{t}=\left(\frac{1-\phi_z^{G*}}{1+\phi_y^{G*}}\right)^{t} \tag{12}$$

$$\mathrm{TCPI}^{G}\left(.^{t+1}\right)=\left[\frac{(Z-\phi_z^{G*}Z)/(Y+\phi_y^{G*}Y)}{Z/Y}\right]^{t+1}=\left(\frac{1-\phi_z^{G*}}{1+\phi_y^{G*}}\right)^{t+1} \tag{13}$$

Here we define the NGMCPI based on the global production technology as follows:

$$\mathrm{NGMCPI}(X^S,Y^S,Z^S)=\frac{\mathrm{TCPI}^{G}(X^{t+1},Y^{t+1},Z^{t+1})}{\mathrm{TCPI}^{G}(X^{t},Y^{t},Z^{t})} \tag{14}$$

Similar to the GML index, the NGMCPI measures the $CO_2$ emission performance dynamic changes from period $\mathbf{t}$ to $t+1$. We can decompose the NGMCPI into two components: a technical efficiency change (EC) index and a technological change (TC) index of $CO_2$ emission performance. The decomposition process is as follows:

$$\begin{aligned}\mathrm{NGMCPI}(t,t+1)&=\frac{\mathrm{TCPI}^{G}(X^{t+1},Y^{t+1},Z^{t+1})}{\mathrm{TCPI}^{G}(X^{t},Y^{t},Z^{t})}\\&=\left[\frac{\mathrm{TCPI}^{C}\left(.^{t+1}\right)}{\mathrm{TCPI}^{C}\left(.^{t}\right)}\right]*\left[\frac{\mathrm{TCPI}^{G}\left(.^{t+1}\right)/\mathrm{TCPI}^{C}\left(.^{t+1}\right)}{\mathrm{TCPI}^{G}\left(.^{t}\right)/\mathrm{TCPI}^{C}\left(.^{t}\right)}\right]\\&=\underbrace{\left\{\frac{\left(\frac{1-\varphi_z^{C*}}{1+\varphi_y^{C*}}\right)^{t+1}}{\left(\frac{1-\varphi_z^{C*}}{1+\varphi_y^{C*}}\right)^{t}}\right\}}_{EC}*\underbrace{\left\{\frac{\left(\frac{1-\varphi_z^{G*}}{1+\varphi_y^{G*}}\right)^{t+1}/\left(\frac{1-\varphi_z^{C*}}{1+\varphi_y^{C*}}\right)^{t+1}}{\left(\frac{1-\varphi_z^{G*}}{1+\varphi_y^{G*}}\right)^{t}/\left(\frac{1-\varphi_z^{C*}}{1+\varphi_y^{C*}}\right)^{t}}\right\}}_{TC}\end{aligned} \tag{15}$$

The EC term in equation (15) is a measure of the “catch-up” effect in terms of $CO_2$ emission performance over the period between $\mathbf{t}$ and $t+1$. It reflects how close a DMU moves toward the contemporaneous production technology. If $EC>1$, it indicates the DMU obtains efficiency gain. The TC reflects change in the frontier shift between the contemporaneous technology and the global technology over the period between $t$ and $t+1$. If $TC>1$, it reflects that the contemporaneous technology frontier has shifted toward the global technology frontier, which can be considered as innovation effect.

## 2.2. The composite indicator for $CO_2$ emission allocation

Although historical cumulative $CO_2$ emissions method can achieve a globally equitable carbon emission space (Pan et al,, 2014), it is not conducive to assume reduction responsibility initiatively, nor to achieve reduction targets in an effective way. According to Zhou and Wang (2016), distributing quotas in proportion to historical $CO_2$ emissions reflects fairness and the emission intensity reflects efficiency. Therefore, we comprehensively propose a hybrid method to allocate emission quotas considering fairness and efficiency principle simultaneously. Firstly, based on Index DEA model, we take the proportion of historical cumulative $CO_2$ emissions and the proportion of average $CO_2$ emission performance as outputs to establish each DMU's efficiency: R1.1

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\begin{aligned}
&\theta^* = \max\ w_E\theta_E + w_P\theta_P \\
&\text{s.t.}\ \sum_{j=1}^{n}\lambda_j Y_{Ej} \geq \theta_E Y_{E_0}, \\
&\quad \sum_{j=1}^{n}\lambda_j Y_{Pj} \geq \theta_P Y_{P_0}, \\
&\quad \sum_{j=1}^{n}\lambda_j = 1,\ \lambda_j \geq 0, \\
&\quad j = 1,\ldots,n,\ \theta_E \geq 1, \theta_P \geq 1.
\end{aligned}
\tag{16}
$$

where $\theta^*$ means the efficiency, $w_E$ and $w_P$ are predetermined weights, here we set $w_E = 1/5$ and $w_P = 4/5$. $Y_P$ means the proportion of historical cumulative $CO_2$ emissions to total sample cities' historical cumulative $CO_2$ emissions and $Y_E$ is the proportion of average $CO_2$ emission performance index to total sample cities' average $CO_2$ emission performance index. There are $n$ DMUs.

$$
C_j = \frac{\theta_j}{\sum_{j=1}^{N}\theta_j} \times C \tag{17}
$$

where $C_j$ represents the composite allocation indicator for city $j$. $\theta_j$ means the efficiency of reducing $CO_2$ emissions and enhancing $CO_2$ emission performance for city $j$, which can be calculated from model (16). $C$ is the $CO_2$ emission quota obtained by sample cities in the given year.

## 3. Empirical study

### 3.1. Data

We now employ models described in section 2 to investigate the total-factor $CO_2$ emission performance and its dynamic change. We select Chinese 71 cities in 2005-2012. In order to derive $CO_2$ emission performance indicator, we first have to R3.3 define the input and output variables explicitly. Combining the relevant indicators such as economic activity, energy consumption and $CO_2$ emissions in DEA model for total-factor performance evaluation is a holistic point (Ramanathan, 2002). According to the basic economic theory of production, an economic entity uses capital, labor and energy as inputs to produce certain amount of products, representing desirable output, and $CO_2$ emissions, an undesirable output (Zhang and Wei, 2015). The similar production framework has been widely adopted to $CO_2$ emission performance evaluation (see Zhou et al., 2010; Zhang et al., 2013; Yao et al., 2015; Wang et al., 2017). Therefore, in this paper, our inputs are labor, capital stock and energy consumption. Desirable output is urban gross domestic product and undesirable output is $CO_2$ emissions. Data are taken from the China City Statistical Yearbook and each city's Statistical Yearbook.

As for inputs, employed labor force numbers for each city are used as the labor input data. Capital stock is selected to represent the capital input. As capital stock data are not directly available from official sources, conventional method is the perpetual inventory method. Ke (2009) proposed a method to calculate China's urban capital stock. Firstly, he estimated urban industrial capital stock by calculating the net value of industrial current assets and fixed assets in the base period. Secondly, using the proportion of industrial added value to GDP, he calculated urban capital stock in the base period. Thirdly, he assessed the following period capital stock according to the actual total investment with perpetual inventory method: $K_{i,t} = (1-\delta)K_{i,t-1} + I_{t-1} / d_{i,t-1}$ where $K_{i,t}$ , $\delta$ represents the capital stock and depreciation rate at time $t$ , respectively. He assumed the depreciation rate was 5%. $I_{t-1}$ represents investment of fixed assets in period $t-1$. We use this method to calculate urban capital stock. The monetary variables, including urban gross domestic product and capital stock, are converted into 2005 constant prices. As urban energy consumption data can not be directly acquired and industrial energy consumption accounts a large proportion of urban energy consumption, we use urban industrial energy consumption data to reflect urban energy consumption. Energy input includes ten main primary fossil energy consumption, including coal, cleaned coal, coke, crude oil, gasoline, kerosene, diesel oil, fuel oil, liquefied petroleum gas and natural gas, transformed into standard coal equivalents.

As for undesirable output, $CO_2$ emissions are calculated based on the the energy consumption amount and IPCC carbon emissions factors for different fossil fuel types:

$$CO_2 = \sum_{i=1}^{n} CO_{2,n} = \sum_{i=1}^{n} E_i \times NCV_i \times CEF_i \times (44/12) \qquad (18)$$

where $CO_2$ indicates the total $CO_2$ emissions amount for a city. $E_i$ represents the consumption amount of fuel $i$. $NCV_i$ is the average caloric value of fuel $i$. $CEF_i$ is the carbon content per calorie of fuel $i$, which can be obtained from IPCC. Table 1 presents descriptive statistics for the sample data.

**Table 1 Descriptive statistics of inputs and outputs, 2005-2012**

| Variable | Unit | Mean | St Dev | Minimum | Maximum |
|---|---|---|---|---|---|
| Capital | $10^8$ Yuan | 6061.07 | 6147.53 | 236.02 | 40761.50 |
| Labor | $10^4$ persons | 164.19 | 169.25 | 5.58 | 1338.68 |
| Energy | $10^4$ Tons of standard coal equivalent | 1225.23 | 874.54 | 95.49 | 4930.04 |
| GDP | $10^8$ Yuan | 2183.45 | 2085.91 | 43.01 | 15365.90 |
| $CO_2$ | $10^4$ Tons | 3336.07 | 2316.14 | 231.14 | 13198.26 |

### 3.2. Static total-factor $CO_2$ emission performance

The Appendix Table A.1 shows the empirical results of static $CO_2$ emission performance from 2005 to 2012 of 71 Chinese cities. The result indicates that Chinese urban have poor energy utilization efficiency and still have high $CO_2$ emissions as the annual average $CO_2$ emission performance index of total sample cities are lower than 0.5. The pressure of energy conservation and emission reduction are great. It is mainly due to Chinese rough development path, which sacrifices the environment in exchange for economic growth. Economic growth increases energy consumption while local government ignores environment governance, which leads to poor $CO_2$ emission performance. In addition, $CO_2$ emission performance of Chinese cities shows instability feature by the emergence of rising and falling. It suggests that, although Chinese government turn to environment governance and promote urban R2.2

$CO_2$ emission performance in recent years, relevant policy formulation and implementation, green technology introduction and absorption are relatively weak. We need to further increase the regulation intensity and improve supporting facilities to effectively achieve emission reduction targets.

Specifically, from the area perspective, Chinese cities have different static $CO_2$ emission performance. We find that Guangzhou, Huizhou, Zhaoqing, Suzhou, Putian, Qingdao, Xianning and Jiayuguan have always been the benchmarks for lying on the frontier during the whole period, which have achieved the best $CO_2$ emission performance. Except for Xianning and Jiayuguan, the rest six cities on the frontier are the eastern cities. Xianning is one of the low carbon economy pilot cities in Hubei province. Its $CO_2$ emissions is around 6.7 million tons while its GDP is about 3.7 billion yuan during the period. Thus, Xianning develops its economy with low $CO_2$ emissions. Jiayuguan has small economy scale with GDP around 0.7 billion yuan. Its environment pollution is not serious during the industrial development. On the contrary, the central and less developed western cities such as Zunyi, Lanzhou and Xianyang, their $CO_2$ emission performance are below 0.2 during the whole sample years. These cities' $CO_2$ emission performances are poor and they have greater emissions reduction potential. R2.2

We divide all 71 sample cities into eastern, central and western regions according to their geographical location. According to Fig.1, the annual average $CO_2$ emission performance in the eastern region is the highest in every sample year, which is higher than the national average value. However, the average $CO_2$ emission performance of both central and western regions are lower than the national average value, especially the western region has the lowest value. In general, the eastern region outperforms the central region and the western region performs worst, which is similar to the results by Yao et al.(2015). These results may be caused by unreasonable industrial structure of the central and western regions. We can adjust industrial structure and introduce advanced production technology to achieve a larger reduction space in the central and western regions. R2.2

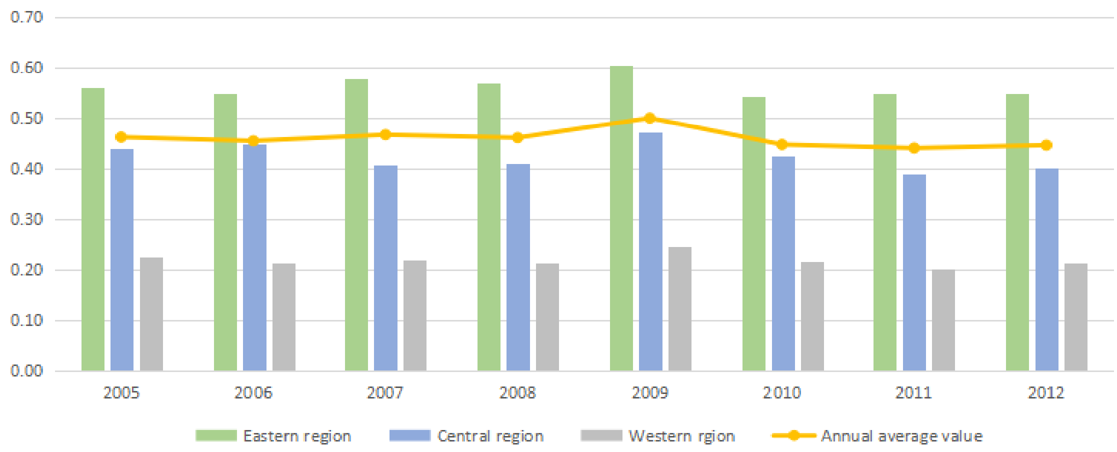


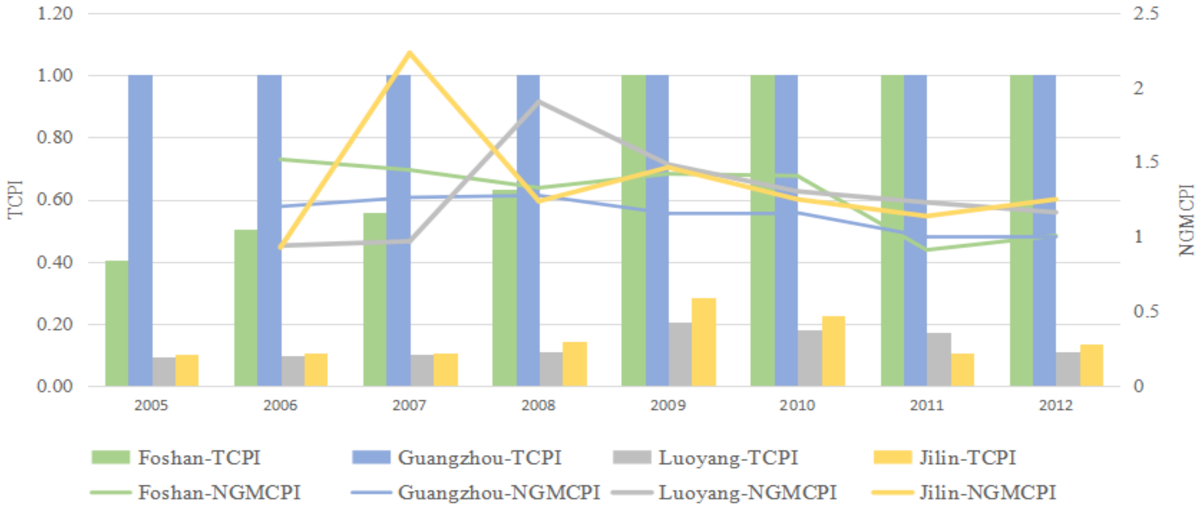

**Fig.1. Average TCPI in three regions, 2005-2012** R2.2

### 3.3. Dynamic change of total-factor $CO_2$ emission performance

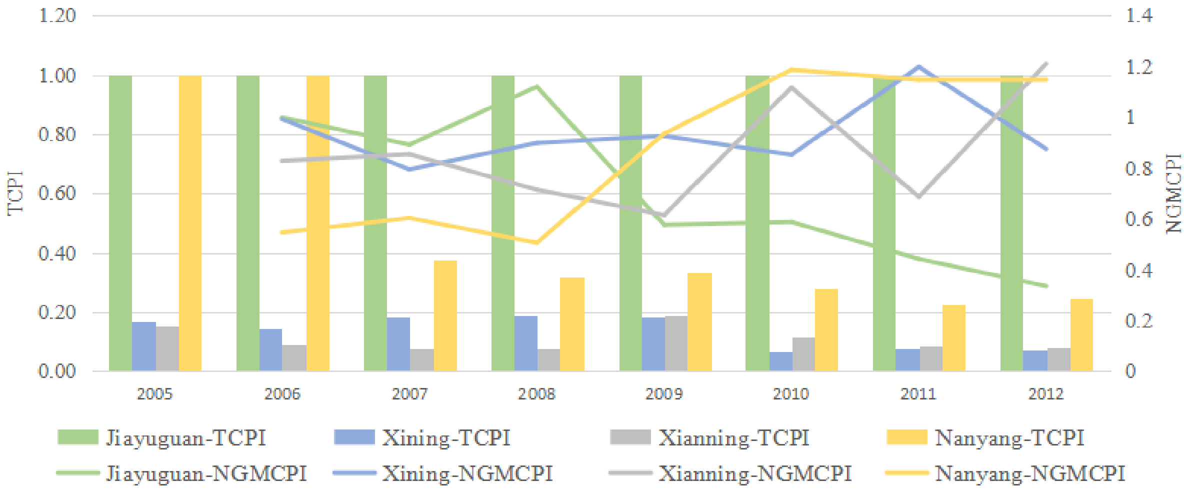
The results of $CO_2$ emission performance dynamic change (NGMCPI) from 2005 to 2012 of 71 Chinese cities are showed in Appendix Table A.2. The NGMCPI increases by approximately 0.079 unit on average from 2005 to 2012. Based on Eq. (14), this indicates that, on average, the ratio of target carbon intensity to actual carbon intensity increases by 7.89% per year over the sample period. In the longitudinal aspect, the average NGMCPI increases in most years except 2005-2006. Chinese urban $CO_2$ emission performance has a stable growth during the sample period, while it has been significantly improved since 2010. We can indicate that although the static $CO_2$ emission performance is not well, Chinese urban $CO_2$ emission performance has been significantly improved. In Chinese "11th Five-Year" plan (2006-2010), energy conservation and emission reduction is treated as an important breakthrough in adjusting economic structure and accelerating transformation of economic development mode. During "11th Five-Year" period, Chinese government implements key projects of energy conservation and emission reduction, improves energy efficiency, and promotes low carbon technology (Price et al., 2011). Subsequently, in "12th Five-Year" plan (2011-2015), Chinese government indicated that, with the accelerated process of industrialization and urbanization, resource and environmental constraints will be increasingly strengthened in China, we still need to strengthen pollutants reduction and improve energy efficiency. All those policies improve Chinese urban $CO_2$ emission performance. Due to a certain delay of policy implementation (Tang et al., 1997), $CO_2$ emission performance has been improved greatly until 2010. R2.2

Specifically, there exists a large difference of NGMCPI among cities. Among all 71 cities, 11 cities show a downward trend in the NGMCPI. Jilin shows the largest growth in the average $CO_2$ emission performance index during the sample period (0.36), while Jiayuguan shows the largest decrease in $CO_2$ emission performance (-0.29). For specific city, we select eight cities to show their TCPI and NGMCPI trends, whose TCPI and NGMCPI have huge differences. From Fig.2(a), we find that Foshan, Guangzhou, Luoyang and Jilin, their average NGMCPI value increase by 29.19%, 15.16%, 28.53% and 35.74%, respectively. On the contrary, from Fig.2(b), Jiayuguan, Xining, Xianning and Nanyang, their average NGMCPI value decreases by 29.19%, 6.55%, 13.86% and 13.20%, respectively. Due to imbalance development of regional economy, regional industrial layouts and industrial energy efficiency are quite different among cities. Therefore, urban initial $CO_2$ emission performances are different, which leads to huge difference of urban dynamic $CO_2$ emission performance. City like Jilin has low TCPI value, but its $CO_2$ emission performance has been improved recently. On the contrary, although city like Jiayuguan has good TCPI value, its $CO_2$ emission performance decreases heavily. It indicates that central government needs to consider common but differentiated emission reduction responsibility to allocate $CO_2$ emission quotas when they are formulating energy conservation and emission reduction policies. Local government also need to make $CO_2$ reduction policies according to their actual GDP, labor conditions, energy consumption structure and $CO_2$ emission performance. R2.2 R2.2

In order to investigate the sources of $CO_2$ emission performance change, we decompose the NGMCPI into two parts, namely, efficiency change (EC) and technical change (TC). Appendix Table A.3 shows the EC values of each city in 2005-2012. Decomposition results show that the average efficiency change (EC) index of $CO_2$ emission performance from 2005 to 2012 is 1.01, showing an average annual increase of 0.12%. In 2005-2006, 2009-2010 and 2010-2011, average efficiency change suffers a decline of 2.96%, 15.40%, 5.13%, respectively. It indicates that Chinese cities do not shift toward the contemporaneous technology frontier. It does not show obviously "catching up" effect in low carbon development. Efficiency change does not have a positive impact on Chinese urban $CO_2$ emission performance change. In the process of low carbon city development, Chinese government needs to make appropriate institutional arrangement and strengthen the exchange and diffusion of technology experience to improve the technological efficiency. All these efforts can realize "catching up" effect in the low carbon development and enhance urban $CO_2$ emission performance.




(a) **TCPI and NGMCPI for Foshan, Guangzhou, Luoyang and Jilin.**




(b) **TCPI and NGMCPI for Jiayuguan, Xining, Xianning and Nanyang** R2.2

**Fig.2. TCPI and NGMCPI Trend Comparison**

For individual cities, 48 cities show an increase in EC. It suggests that these cities move toward the contemporaneous technology frontier over the study period and catch up in attaining low-carbon development. However, EC decrease in 23 cities. Nanyang has the lowest average EC value of 0.86, while Foshan has the highest average EC value of 1.15. This indicates that the Foshan is working hard to catch up R2.2 with the more well-performance cities, whereas Nanyang's improvement in $CO_2$ emission performance have been delayed in comparison to other cities. It also illustrates that efficiency changes of Chinese cities are very different. Some cities'

$CO_2$ emission efficiency has been improved, technology diffusion and exchange system arrangement has been optimized. There are still some cities need to make more efforts to enhance efficiency improvement in order to reduce or even reverse the negative impact of efficiency change on $CO_2$ emission performance change. As cities have different levels of economic development, there exists difference in policy formulation and implementation for local government. Some cities still pursuit unilateral economic growth at the expense of environment quality, resulting insignificant “catching up” effect of low carbon technology.

Appendix Table A.4 shows the TC value of each city in 2005-2012, reflecting low carbon technology change of each city. We find that average technical change of $CO_2$ emission performance change in the sample period is 1.12, which indicates a general technological progress by 12% toward low-carbon technology. Results show that the contemporaneous frontier approaches to the global frontier in general and technology are promoted in Chinese cities during the research period. During the sample period, technical progress is observed in all years except 2008-2009. The technical recession is observed in 2008-2009, it may be due to the subsequent influence of financial crisis in 2008 (Xie et al., 2014). After the financial crisis outbreaks, Chinese industrial structure has certain degradation, which leads to the technology degradation. Overall, Chinese urban have made great progress of low carbon technology. In “11th Five Year” plan, Chinese government propose that, during the construction process of “resource-conserving and environmental-friendly society”, we need to further optimize industrial structure, make substantial technological progress and change the growth mode. And in the “12th Five-Year Plan”, it is clearly proposed that we have to adjust and optimize industrial structure, popularize advanced technology, introduce and absorb abroad advanced technology. Then we can improve energy efficiency and reduce pollution emissions. Under the guiding and regulation of these policies, Chinese urban $CO_2$ reduction technology has made significant improvement. R2.2

It is found that most cities’ average annual TC values are above unity, which indicates a increase in technological change of $CO_2$ emission performance change. Among these cities, Jilin, Yulin, Xianyang and Lanzhou have the largest technology progress. Only five cities have technology retrogression. Wenzhou, Putian, Xianning, Zhongshan and Jiayuguan, their average TC value decreases by 1.25%, 6.19%, 13.86%, 1.97% and 29.19%, respectively. It indicates that although Chinese government has made energy conservation and emission reduction deployment in general, there exists a big difference on low carbon technology improvement for Chinese cities, as economic development, industrial structure and initial technology of each city are different. For the initial technical level of central and western cities are low, they are much easier to enhance technical imitation and innovation ability in the process of low carbon technology improvement.

We examine the trends in dynamic total-factor of $CO_2$ emission performance as well as its decomposition. Fig.3 shows the average changes of NGMCPI and its decomposition parts (EC and TC) during 2005-2012. From Fig.3, we find that NGMCPI value is always above unity. It shows a stable increasing trend from 0.96 at the beginning to 1.14 in the final period. Therefore, urban $CO_2$ emission performance has been effectively improved during the sample period. Only in 2008-2009 is there a noticeable downward trend. It may due to the subsequent impact of Chinese industrial structure degradation after the 2008 financial crisis. It leads to technical degradation, which has negative impact on $CO_2$ emission performance change.

The results of decomposition show that both EC and TC seem to be responsible for the change in urban $CO_2$ emission performance change and they have adverse effect on the NGMCPI. The EC index fluctuates in the sample period, it increases between 2006 and 2008, then decreases significantly in 2009-2011. The TC index in 2008-2009 decreases significantly lower than unity, which may be affected by financial crisis in 2008. In the rest years, the TC values are greater than unity, and technical progress effect of $CO_2$ emission performance in Chinese cities is obvious. It means that urban technology innovation has been enhanced. It is similar to the results of Chen and Golley (2014), they indicate that China has developed cleaner production processes and green technology innovation since the beginning of the 90's. Except for the period of 2011-2012, the changes of NGMCPI in the rest sample years coincide with TC change trends. This suggests that the increase in $CO_2$ emission performance is mainly driven by technological innovation. Under the "11th Five-Year" plan (2006-2010) and "12th Five-Year" plan (2011-2015), the Chinese government proposed reduction targets for energy and carbon intensity. Therefore, cities were under considerable pressure to reduce its carbon emissions. Based on our results, $CO_2$ emission performance has been improved significantly driving by technical R2.2

innovation, it indicates obvious effect of the carbon policy on green technology and innovation.

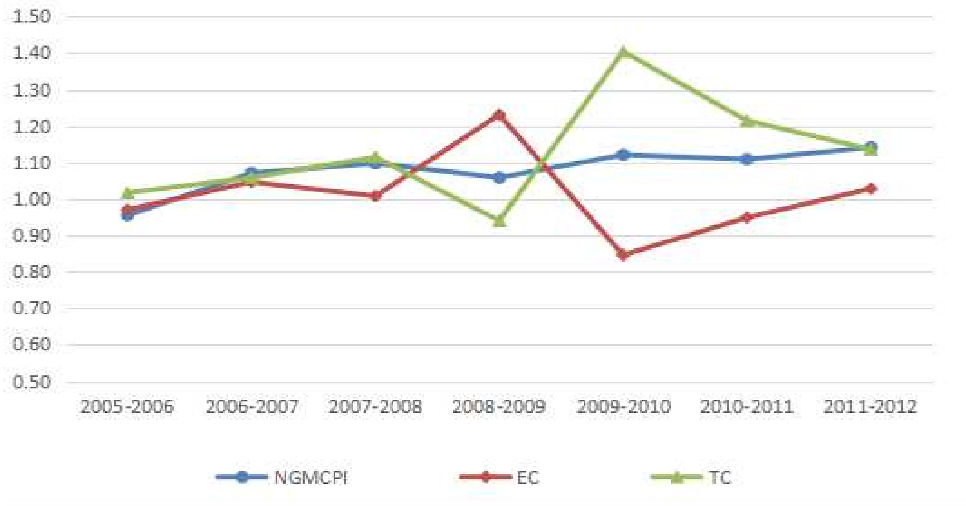



**Fig.3. Changes of NGMCPI,EC,TC, 2005-2012**

Fig.4-6 show the trends in the NGMCPI and its decomposition for the three regions. The average NGMCPI of the eastern, central and western regions is 7.75%, 9.58% and 6.89%, respectively. It shows almost identical NGMCPI trends in these three regions. In the initial stage of 2005-2006, annual average NGMCPI in these three regions are below unity, while the NGMCPI value of rest years for all regions have substantial growth, greater than unity. It indicates that the $CO_2$ emission performances of whole regions are improved. The NGMCPI values of the central region increases significantly, especially during the period of 2006-2009. In “11th Five-Year” plan, government proposes to optimize industrial structure, develop circular economy and improve resource comprehensive utilization in order to realize the “rise of central China plan”. The strategy leads to better industrial structure and energy efficiency, which helps to improve $CO_2$ emission performance.

The improvement of western region is obvious. The NGMCPI values of the western region is always below eastern and central regions during 2005-2008, while in 2009-2011 it increases substantially, even exceed the eastern and central regions. It indicates that $CO_2$ emission performance of the western region is significantly improved in recent years. The “11th Five-Year” plan for western development clearly put forward to improve development quality, optimize resources allocation, and strengthen resource conservation and comprehensive utilization. The implementation of these policies drives $CO_2$ emission performance of the western region improved. As the infrastructure in the western region is weak, the implementation of these policies have certain delay, advanced technology also need time to play a role. Therefore, $CO_2$ emission performance began to make significant improvements in the western region in recent years, even succeed the eastern and central regions.

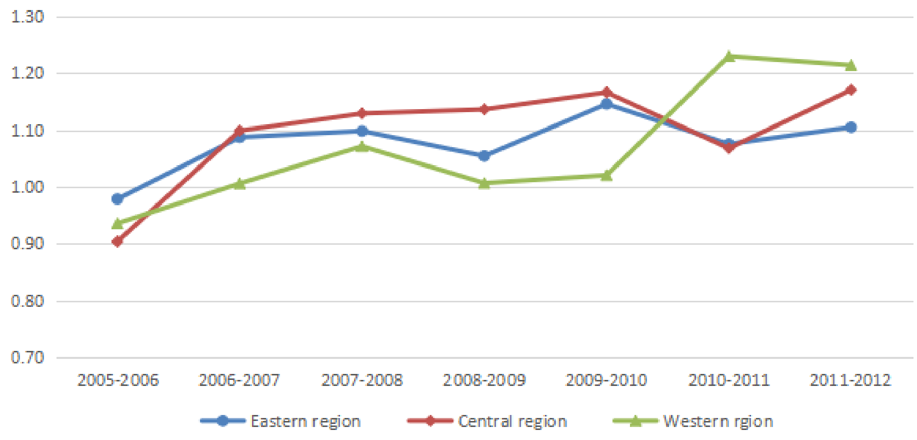



**Fig.4. The changes of NGMCPI in eastern, central, western region**

In terms of its decomposition, from Fig.5 we find that the EC of three regions show a similar trend, with a large increase in 2008-2009, a decrease in 2009-2010 and then show different rate of growth. The EC values of all the regions are below unity in 2009-2011. Efficiency change has a negative impact on $CO_2$ emission performance change. The largest EC is observed during 2008-2009. The EC values of three regions have large growth in 2008-2009. In order to achieve the binding target of a 20% reduction of unit of GDP energy consumption proposed in the "11th Five-Year Plan", National Development and Reform Commission propose "comprehensive program of energy conservation and emission reduction". They clearly divide emission reduction responsibility and establish a strong coordination mechanism of energy conservation and emission reduction. Therefore, EC values of three regions increase greatly in 2008-2009.

Specifically, EC value of the western region is not better than the rest two regions in the whole period except 2007-2009. The western region is obviously lagged behind R2.2
in efficiency of low carbon management. The EC of the western region fluctuates more than that of the other regions. This may be due to the management system and regional coordination of the eastern and central regions are better than the western region, which leads to energy conservation and emission reduction efficiency better. As Zhang and Wei (2015) proposed, the western region is well known for its rich R2.2
natural resources but has lagged behind the other regions because lack of infrastructure and economic growth speed. It leads to low efficiency in low carbon

development.

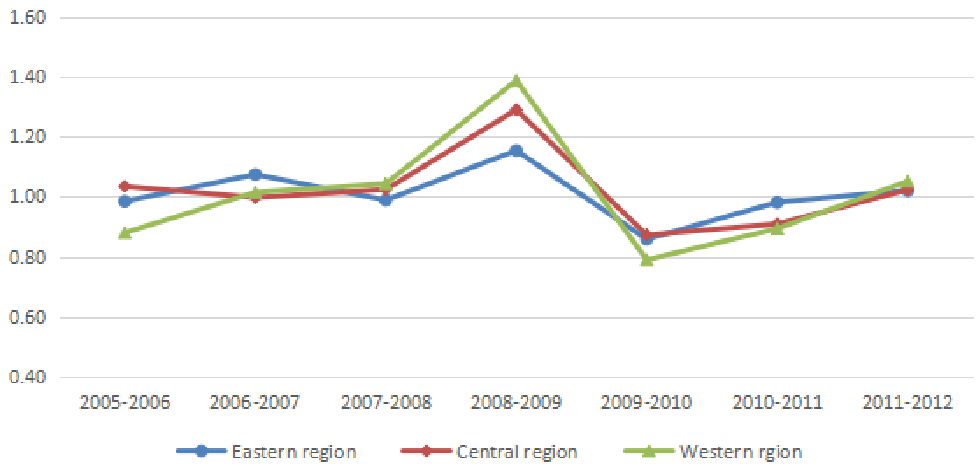



**Fig.5. The changes of EC in eastern, central, western region**

Except that TC of three regions in 2008-2009 are less than unity, TC are above unity in the rest years among three regions. It implies that low carbon technological innovation continues in all three regions throughout the period except during 2008-2009, cities vigorously develop low carbon production technology. TC value falls sharply in 2008-2009. It may be due to the impacts of financial crisis in 2008. Due to industrial structure degradation and economic downturn caused by the financial crisis in 2008, it results technical innovation investment and concern of environmental issues degraded in the following year, which leads to technical degradation.

TC of the central region is enhanced substantially, even exceed the eastern region. Meanwhile, western region's technology has been enhanced, it has greater progress than the eastern and central regions in 2009-2012. The western region is leading in the innovation of low carbon technology in 2009-2012. It indicates that, although the central and western regions have poor technology basis, low carbon technology innovation of the central and western regions are strengthened in recent years. It may be related to the backward technology basis, and there is a big gap compared with the eastern region. The technology progress is proposed as a guide in the "rise of the central China plan". Since the western region was aimed to build key economic regions and key ecological areas in the western "12th Five-Year" plan, it focused on enhancing the capability of independent innovation, taking into account of ecological environment improvement. All those policies enhanced technology innovation capabilities of the eastern and western regions.

Compared Fig.4-Fig.6, We find that the change trends of NGMCPI in the eastern and western regions coincide with its EC change trends in 2005-2006, whereas it coincide with TC change trends in 2007-2012. EC and TC in the eastern and western regions are similar, but due to different change degree, there is a difference in the $CO_2$ emission performance change of the eastern and western regions. It implies that $CO_2$ emission performance change is mainly driven by efficiency change and technology innovation in eastern and western regions. It is suggested that the role of government and innovation are quite important for sustainable development in these regions. NGMCPI of the central region coincide with its TC change trends in the whole period. It implies that total-factor $CO_2$ emission performance change of central region is mainly affected by the technology innovation. The government needs to do more work to promote technology that can increase the overall $CO_2$ emission performance for this region. R2.2 R2.2

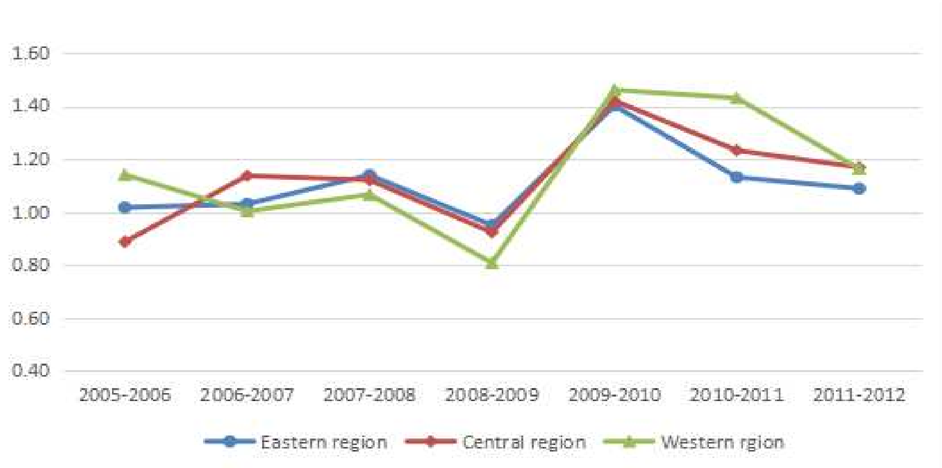



**Fig.6. The changes of TC in eastern, central, western region**

For comparative purposes, we also compute the TCPI, NGMCPI and its decomposition based on the Shephard technology which uses single abatement factor. As shown in Fig.7, the results for TCPI under the Shephard technology show a relatively high $CO_2$ emission performance during the whole sample year. This difference may be due to the use of different production technology. Without considering different DMU's pollution treatment capacity, Shephard technology using a single abatement factor might lead to the overestimation of $CO_2$ emission performance in this case. R2.2/2.3

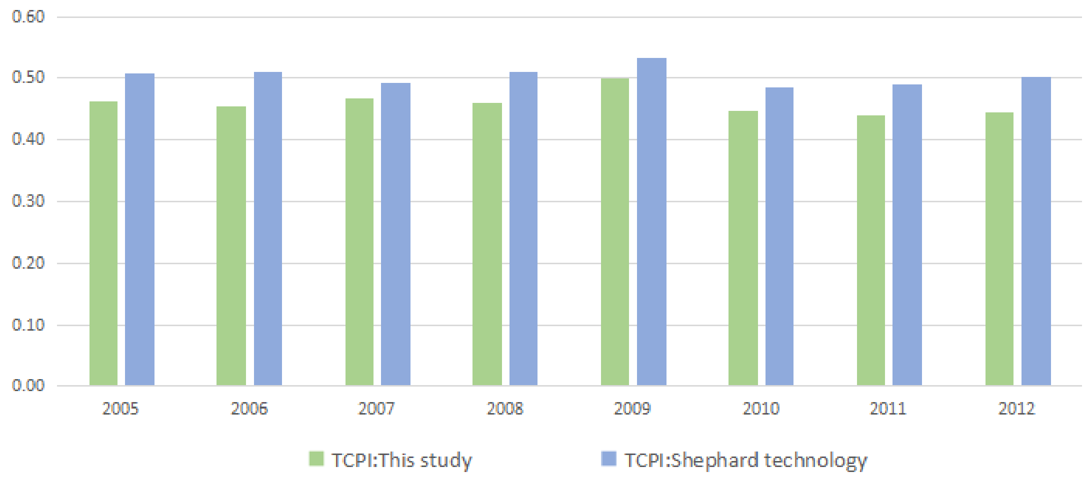
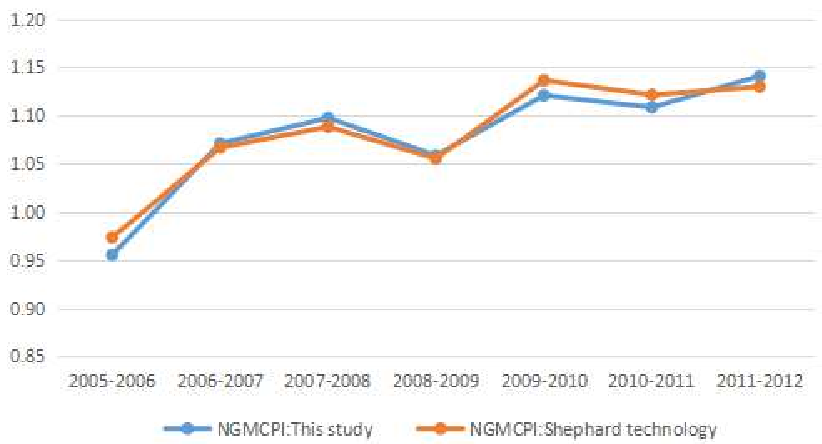
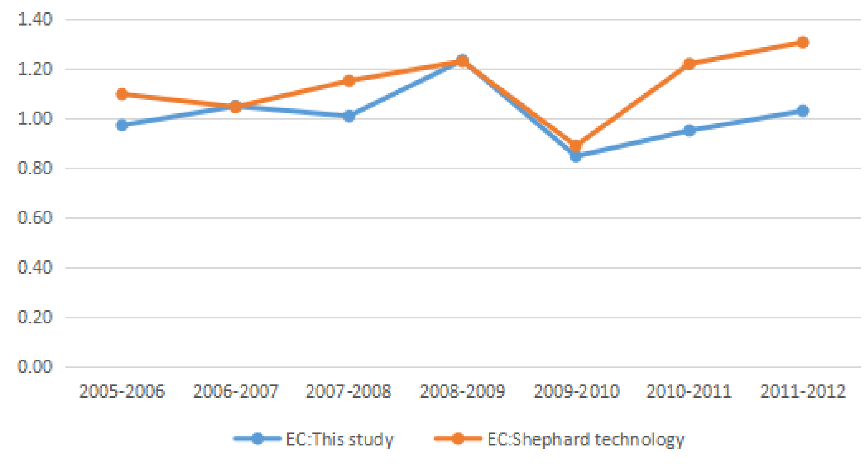



**Fig.7. Comparison of TCPI under different production technology**

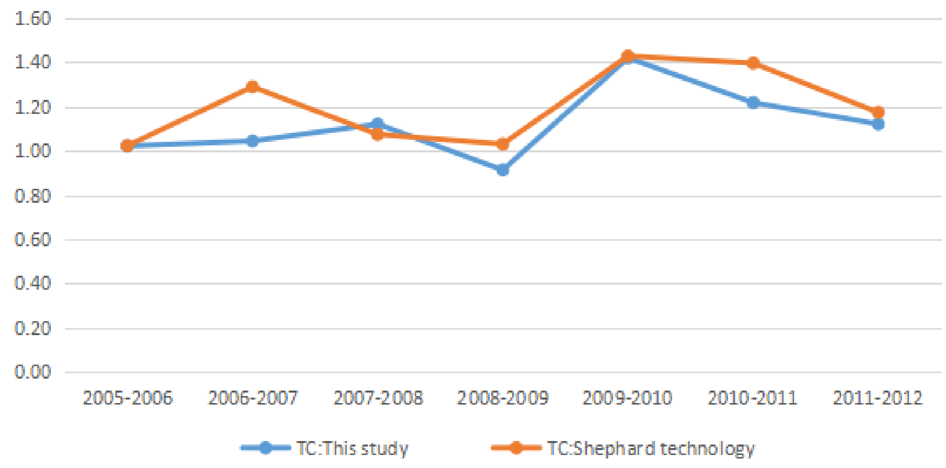
As shown in Fig.8, we find that NGMCPI under the Shephard technology show similar results compared with the results in this paper . It shows an average annual increase of 8.16%, which is higher than that in this study (average annual growth=7.89%). The decomposition also show similar trends under the two production technologies. Both the EC and TC under the Shephard technology are higher than the results in our study. As discussed earlier, the Shephard technology uses single abatement factor and it might lead to overestimation. The comparison results confirm the necessary and significant of our method. Meanwhile, the similar trend of NGMCPI and its decomposition under the Shephard technology ensure the robustness of previous results in our study. R2.2/2.3




(a)




(b)




(c)

**Fig.8. Comparison of NGMCPI and its decomposition under different production technology**

### 3.4. $CO_2$ emission allocation

On the eve of the Copenhagen climate conference in 2009, Chinese government made a mandatory goal of a 40-45% decrease in carbon intensity by 2020 compared to the 2005 level. A Chinese CO2 emission was 5401.14 million tons in 2005, and the GDP was 18457.58 billion Yuan. The carbon intensity was 2.93 t $CO_2/10^4$ Yuan. We assume that by 2020 Chinese carbon intensity will be decreased by 45% compared to the 2005 level. Therefore, the carbon intensity will fall to 1.61 t $CO_2/10^4$ Yuan in 2020. Meanwhile, we assume that from 2005 to 2020, the GDP has an annual growth rate of 8%, then in 2020 the GDP is about 585505.7 billion Yuan. The total amount of $CO_2$ emissions in 2020 will be 9426.7 million tons.

According to the historical cumulative $CO_2$ emissions of 71 sample cities in

2005-2012 and the national historical cumulative $CO_2$ emissions in 2005-2012, we need to allocate 3700.6 million tons $CO_2$ quotas for 71 sample cities in 2020. We obtain the allocation indicator under the composite indicator principle based on formula (16)-(17). According to Zhou and Wang (2016), the historical cumulative emissions indicator reflects fairness principle while the emission intensity reflects efficiency principle. In order to find the differences among different allocation principle, we also calculate the emission quotas under the historical cumulative emissions indicator and the $CO_2$ emission performance indicator, respectively. The results are shown in Table 2. In this table, we also illustrate each city's historical cumulative $CO_2$ emissions and their average $CO_2$ emission performance index during 2005-2012. R2.2/2.3

The method of historical cumulative $CO_2$ emission is in accordance with the grandfathering criterion, which implies that more historical $CO_2$ emission follows more emission quotas (Zhou and Wang, 2016). The results show that, under historical cumulative $CO_2$ emissions method, cities with more quotas are mainly concentrated in the eastern region as the eastern cities like Beijing, Tianjin and Guangzhou have high $CO_2$ emissions. Under this principle, there is a great gap of $CO_2$ emission quotas between cities. Tianjin has the highest $CO_2$ emission quota with 151.55 million tons, while Huizhou has the minimum quota with only 3.98 million tons. Based on the allocation method of cumulative historical $CO_2$ emissions, it only considers historical energy consumption and emissions, cities with high $CO_2$ emissions can obtain more $CO_2$ emission quota. Such allocation method does not consider the $CO_2$ reduction potential among different cities. This allocation principle may encourage cities increasing emissions in order to get more emission quotas. Cities which have large mitigation potential would not be positive to make carbon emission reduction. It is not conducive to promote large emitters to reduce their energy consumption and $CO_2$ emissions. R2.2/2.3

We find that cities with high emission performance can obtain more emission quotas under the efficiency principle. Cities like Suzhou, Qingdao and Wenzhou can obtain more than one million ton emission quotas, whereas their emission quotas under the cumulative historical emissions method are relatively low. As cities with high $CO_2$ emission performance have good energy utilization efficiency, their mitigation potential are relatively small and they can undertake less reduction targets. Cities with low $CO_2$ emission performance have huge mitigation potential, more R2.2/2.3

reduction responsibility allocated to them can enhance the reduction efficiency. However, Chinese regional development are fairly imbalanced in terms of economic level, geographical factors, natural resources and industry structure (Yu et al., 2012; Zhang et al., 2014). Such allocation method ignores different energy structure and energy consumption among cities, which may lead to unfair quota distribution. R2.2/2.3

In this paper, we consider historical $CO_2$ emissions and $CO_2$ emission performance as the outputs, then use Index DEA model to calculate composite index for emission quotas allocation. The results indicate that the $CO_2$ emission quotas locate between those under the historical $CO_2$ emission method and the emission performance method. Below we explain the rationality of our allocation results.

As shown in Table 2, cities with low historical $CO_2$ emissions and good $CO_2$ emission performance get more emission quotas, whereas cities with high $CO_2$ emissions and poor $CO_2$ emission performance obtain less emission quotas. For example, the average $CO_2$ emission performance in Zhaoqing and Huizhou are both R2.2/2.3 unity, their historical cumulative $CO_2$ emissions are 29.04 million tons and 19.73 million tons, respectively. The average $CO_2$ emission performance in Baotou and Jilin are both 0.15, their historical cumulative $CO_2$ emissions are 457.68 million tons and 425.91 million tons, respectively. Under our composite index method, Zhaoqing and Huizhou obtain 89.30 milliton tons and 80.73 million tons quotas, respectively. However, Baotou and Jilin get 16.89 million tons and 17.46 million tons emission quotas, respectively. We allocate high emission quotas to cities with low historical $CO_2$ emissions and good $CO_2$ emission performance. These cities are able to sell their extra emission quotas and obtain revenue after they meet the requirements of normal production activities. On the contrary, we allocate low emission quotas to cities with high historical $CO_2$ emissions and poor $CO_2$ emission performance. These cities need to buy emission quotas in order to satisfy the emission regulation as well as meet the requirements of normal production activities. Thus, our allocation method stimulates R2.2/2.3 the establishment of carbon trading market, which encourages cities to reduce emissions and enhance emission performance through the market mechanism. Meanwhile, as Chinese government is promoting carbon trading policy and establishing national carbon trading market recently, our allocation method is in line with the current policy trend.

In addition, cities with high historical $CO_2$ emissions can obtain more emission quotas if they have good $CO_2$ emission performance, while they will get less emission quotas if they have poor $CO_2$ emission performance. For example, historical cumulative $CO_2$ emissions in Beijing, Shanghai and Guangzhou are 628.88 million tons, 693.15 million tons and 631.97 million tons, respectively. Average $CO_2$ emission performance in Shanghai and Guangzhou are both unity, whereas average $CO_2$ emission performance in Beijing is only 0.58. Under our composite index method, Beijing obtains almost half emission quotas in Shanghai and Guangzhou. Cities with good $CO_2$ emission performance have less improvement room for technology and less reduction potential, they can get more emission quotas. However, cities with poor $CO_2$ emission performance are able to improve their technology heavily and have huge reduction potential. Thus, our allocation method is rational as it can motivate cities with high historical emissions to reduce their emissions by improving technology when they have poor $CO_2$ emission performance.

**Table 2 The $CO_2$ emission allocation of cities in 2020 (unit: million tons)**

| | CO2 emission quota in 2020 | | | Cumulative $CO_2$ Emissions | Average value of TCPI |
|---|---|---|---|---|---|
| | Cumulative emission indicator | $CO_2$ emission performance indicator | Composite index | | |
| Beijing | 126.83 | 66.34 | 66.80 | 628.88 | 0.58 |
| Tianjin | 156.50 | 42.81 | 94.74 | 776.00 | 0.38 |
| Shijiazhuang | 31.95 | 105.83 | 102.33 | 158.40 | 0.93 |
| Tangshan | 41.79 | 105.25 | 102.93 | 207.19 | 0.93 |
| Handan | 21.24 | 55.58 | 54.28 | 105.34 | 0.49 |
| Zhangjiakou | 9.49 | 47.18 | 44.57 | 47.06 | 0.42 |
| Taiyuan | 38.32 | 23.35 | 23.48 | 189.99 | 0.21 |
| Jincheng | 40.94 | 9.49 | 9.60 | 202.98 | 0.08 |
| Shuozhou | 34.95 | 8.54 | 8.63 | 173.27 | 0.08 |
| Yuncheng | 24.69 | 4.37 | 4.42 | 122.41 | 0.04 |
| Hohhot | 51.53 | 19.85 | 20.03 | 255.49 | 0.17 |
| Baotou | 92.31 | 16.69 | 16.89 | 457.68 | 0.15 |
| Shenyang | 65.00 | 71.16 | 71.06 | 322.31 | 0.63 |
| Dalian | 36.77 | 94.82 | 92.65 | 182.32 | 0.84 |
| Changchun | 47.84 | 63.99 | 63.66 | 237.22 | 0.56 |
| Jilin | 85.90 | 17.26 | 17.46 | 425.91 | 0.15 |
| Siping | 32.30 | 18.50 | 18.62 | 160.14 | 0.16 |
| Harbin | 66.22 | 43.86 | 44.08 | 328.33 | 0.39 |
| Shanghai | 139.80 | 113.50 | 113.80 | 693.15 | 1.00 |
| Nanjing | 46.90 | 66.70 | 66.28 | 232.57 | 0.59 |
| Wuxi | 98.71 | 62.54 | 62.87 | 489.44 | 0.55 |
| Changzhou | 46.66 | 37.25 | 37.35 | 231.35 | 0.33 |
| Suzhou | 64.67 | 113.50 | 112.23 | 320.67 | 1.00 |

| | | | | | |
|---|---|---|---|---|---|
| Nantong | 42.66 | 52.01 | 51.84 | 211.53 | 0.46 |
| Yancheng | 23.26 | 50.40 | 49.54 | 115.31 | 0.44 |
| Zhenjiang | 52.13 | 25.76 | 25.95 | 258.46 | 0.23 |
| Hangzhou | 60.84 | 68.54 | 68.41 | 301.68 | 0.60 |
| Ningbo | 53.77 | 61.87 | 61.73 | 266.59 | 0.55 |
| Wenzhou | 26.54 | 109.62 | 104.77 | 131.58 | 0.97 |
| Jiaxing | 51.35 | 31.43 | 31.61 | 254.59 | 0.28 |
| Huzhou | 32.45 | 27.31 | 27.38 | 160.88 | 0.24 |
| Shaoxing | 45.06 | 43.82 | 43.83 | 223.40 | 0.39 |
| Jinhua | 32.08 | 43.46 | 43.22 | 159.04 | 0.38 |
| Taizhou | 34.47 | 91.16 | 88.99 | 170.93 | 0.80 |
| Hefei | 37.63 | 39.22 | 39.19 | 186.56 | 0.35 |
| Fuzhou | 74.29 | 39.62 | 39.89 | 368.33 | 0.35 |
| Putian | 6.71 | 113.50 | 91.93 | 33.28 | 1.00 |
| Nanchang | 24.27 | 39.79 | 39.42 | 120.32 | 0.35 |
| Jinan | 34.77 | 85.62 | 83.80 | 172.42 | 0.75 |
| Qingdao | 33.32 | 112.74 | 108.90 | 165.20 | 0.99 |
| Jining | 40.24 | 59.86 | 59.43 | 199.54 | 0.53 |
| Weihai | 36.40 | 107.98 | 104.92 | 180.48 | 0.95 |
| Linyi | 91.97 | 24.60 | 24.87 | 456.03 | 0.22 |
| Heze | 44.50 | 13.22 | 13.36 | 220.65 | 0.12 |
| Zhengzhou | 86.57 | 29.96 | 30.25 | 429.25 | 0.26 |
| Luoyang | 116.73 | 15.42 | 15.62 | 578.77 | 0.14 |
| Nanyang | 35.41 | 53.61 | 53.20 | 175.57 | 0.47 |
| Wuhan | 42.11 | 79.24 | 78.21 | 208.81 | 0.70 |
| Yichang | 25.44 | 34.32 | 34.14 | 126.13 | 0.30 |
| Xianning | 10.82 | 113.50 | 99.56 | 53.64 | 1.00 |
| Changsha | 19.69 | 76.96 | 73.79 | 97.63 | 0.68 |
| Guangzhou | 127.46 | 113.50 | 113.67 | 631.97 | 1.00 |
| Zhuhai | 27.81 | 24.87 | 24.90 | 137.88 | 0.22 |
| Foshan | 55.98 | 86.54 | 85.84 | 277.58 | 0.76 |
| Zhaoqing | 5.86 | 113.50 | 89.30 | 29.04 | 1.00 |
| Huizhou | 3.98 | 113.50 | 80.73 | 19.73 | 1.00 |
| Zhongshan | 15.03 | 34.55 | 33.90 | 74.54 | 0.30 |
| Nanning | 10.32 | 39.97 | 38.34 | 51.19 | 0.35 |
| Liuzhou | 43.05 | 13.93 | 14.06 | 213.45 | 0.12 |
| Chongqing | 160.75 | 35.77 | 113.80 | 797.06 | 0.32 |
| Guiyang | 31.29 | 23.12 | 23.20 | 155.13 | 0.20 |
| Zunyi | 37.22 | 13.86 | 13.99 | 184.54 | 0.12 |
| Kunming | 58.86 | 26.80 | 27.01 | 291.87 | 0.24 |
| Xi’an | 32.47 | 38.79 | 38.68 | 161.00 | 0.34 |
| Xianyang | 45.39 | 12.41 | 12.55 | 225.06 | 0.11 |
| Yulin | 101.35 | 4.36 | 4.42 | 502.51 | 0.04 |
| Lanzhou | 92.01 | 8.94 | 9.06 | 456.23 | 0.08 |

| | | | | | |
|---|---|---|---|---|---|
| Jiayuguan | 40.77 | 113.50 | 110.58 | 202.14 | 1.00 |
| Xining | 26.32 | 15.42 | 15.51 | 130.49 | 0.14 |
| Yinchuan | 68.86 | 6.03 | 6.12 | 341.45 | 0.05 |
| Urumqi | 99.07 | 8.32 | 8.43 | 491.25 | 0.07 |

## 4. Conclusions

As pollution control ability and marginal abatement costs in different production units are different, this paper considers multiple abatement factors and proposes total-factor $CO_2$ emission performance index and dynamic change index to calculate 71 cities' $CO_2$ emission performance and its dynamic change from 2005 to 2012. We also compare our results with the Shephard production technology to confirm the necessary and significance of our model. Then, we allocate urban carbon emission quotas in 2020 based on hybrid method, which considers reducing $CO_2$ emissions as well as enhancing $CO_2$ emission performance. We also compare our results with the results under the fairness principle and efficiency principle. Some main conclusions are obtained as follows.

First, Chinese cities have poor energy utilization efficiency and still have high R2.1
$CO_2$ emissions. We need to implement "common but differentiated responsibility" as cities have different $CO_2$ emission performance. Although the static $CO_2$ emission performance is not well, the dynamic $CO_2$ emission performance has been significantly improved. It is driven mainly by technological advances, not the catch-up effect. It indicates obvious effect of the carbon policy on green technology and innovation. After the financial crisis in 2008, the subsequent influence of industrial structure degradation leads to technology degradation. The $CO_2$ emission performance is also influenced by external events. The comparison results illustrate that without considering different DMU's pollution treatment capacity, Shephard technology using a single abatement factor might lead to the overestimation of $CO_2$ emission performance in this case.

Second, considering regional differences, the eastern region outperforms the R2.1
central region and the western region performs worst, whereas the dynamic total-factor $CO_2$ emission performance of the central region has the largest increase. It is followed by the eastern and western regions. The decomposition results show $CO_2$ emission performance change is mainly driven by efficiency change and technology innovation in eastern and western regions. It is suggested that the role of government

and innovation are quite important for sustainable development in these regions. $CO_2$ emission performance change of central region is mainly affected by the technology innovation. The government need to do more work to promote technology that can increase the overall $CO_2$ emission performance for this region.

Finally, the carbon quota allocation results show that our allocation method is rational. Cities with low historical $CO_2$ emissions and good $CO_2$ emission performance get more emission quotas. Meanwhile, we distribute higher emission quotas to cities with high historical $CO_2$ emissions when they have better $CO_2$ emission performance. One the one hand, our allocation method stimulates the establishment of carbon trading market, which encourages cities to reduce emissions and enhance emission performance through market mechanism. Our allocation method is in line with the current policy trend. On the other hand, our allocation method can motivate cities with high historical emissions to reduce their emissions by improving technology when they have poor $CO_2$ emission performance.

Based on the above discussions and conclusions, we can provide some suggestions for policy makers about urban $CO_2$ reduction and quota allocation in China. The Chinese government should promote energy efficiency and overcome the R1.3 regulations and external events that restrict carbon policy's implementation. The Chinese government should promote energy efficiency and overcome the regulations and external events that restrict carbon policy's implementation. Chinese government should encourage enterprises to develop low carbon technology. Clean investments and financial support need to be provided in production process. Meanwhile, the eastern and western cities should facilitate leadership effect and enhance learning capacity as their $CO_2$ emission performance can be affected by catch-up effect. In addition, in urban $CO_2$ emission allocation we need to consider the allocation method from comprehensively perspective as most cities have adjustable room to improve their $CO_2$ emissions and performance. The government should be clear that the city with poor $CO_2$ emission performance and high historical emissions should be given a low emission quota. Such allocation plan can motivate the establishment of carbon trading market. The government should also provide them with certain support to promote the improvement of green technology.

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# Appendix A

**Table A.1** R1.2

TCPI **of 71 cities, 2005-2012**

| Cities | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 |
|---|---|---|---|---|---|---|---|---|
| Beijing | 0.57 | 0.57 | 0.56 | 0.58 | 0.60 | 0.59 | 0.62 | 0.59 |
| Tianjin | 0.40 | 0.40 | 0.38 | 0.38 | 0.38 | 0.37 | 0.35 | 0.36 |
| Shijiazhuang | 0.84 | 0.75 | 1.00 | 0.98 | 1.00 | 0.89 | 1.00 | 1.00 |
| Tangshan | 1.00 | 1.00 | 1.00 | 1.00 | 0.86 | 0.72 | 1.00 | 0.84 |
| Handan | 0.39 | 0.45 | 0.49 | 0.48 | 0.65 | 0.52 | 0.51 | 0.44 |
| Zhangjiakou | 0.42 | 0.43 | 0.41 | 0.40 | 0.63 | 0.36 | 0.35 | 0.33 |
| Taiyuan | 0.16 | 0.22 | 0.23 | 0.21 | 0.21 | 0.21 | 0.20 | 0.21 |
| Jincheng | 0.12 | 0.07 | 0.09 | 0.08 | 0.14 | 0.06 | 0.05 | 0.05 |
| Shuozhou | 0.10 | 0.10 | 0.09 | 0.07 | 0.12 | 0.04 | 0.04 | 0.04 |
| Yuncheng | 0.08 | 0.03 | 0.03 | 0.03 | 0.04 | 0.04 | 0.02 | 0.02 |
| Hohhot | 0.13 | 0.14 | 0.15 | 0.15 | 0.25 | 0.24 | 0.17 | 0.17 |
| Baotou | 0.10 | 0.10 | 0.11 | 0.12 | 0.23 | 0.22 | 0.15 | 0.15 |
| Shenyang | 0.41 | 0.48 | 0.56 | 0.73 | 0.75 | 0.70 | 0.54 | 0.84 |
| Dalian | 0.73 | 0.80 | 0.79 | 0.82 | 0.85 | 0.89 | 0.90 | 0.91 |
| Changchun | 0.42 | 0.50 | 0.52 | 0.55 | 0.66 | 0.65 | 0.57 | 0.63 |
| Jilin | 0.10 | 0.11 | 0.11 | 0.14 | 0.28 | 0.23 | 0.11 | 0.14 |
| Siping | 0.18 | 0.17 | 0.22 | 0.15 | 0.27 | 0.10 | 0.11 | 0.11 |
| Harbin | 0.39 | 0.40 | 0.41 | 0.42 | 0.39 | 0.37 | 0.35 | 0.35 |
| Shanghai | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Nanjing | 0.58 | 0.61 | 0.61 | 0.61 | 0.58 | 0.58 | 0.58 | 0.56 |
| Wuxi | 1.00 | 0.44 | 1.00 | 0.40 | 0.41 | 0.41 | 0.35 | 0.40 |
| Changzhou | 0.35 | 0.35 | 0.36 | 0.33 | 0.33 | 0.30 | 0.31 | 0.30 |
| Suzhou | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Nantong | 0.44 | 0.44 | 0.46 | 0.45 | 0.55 | 0.46 | 0.38 | 0.49 |
| Yancheng | 0.52 | 0.44 | 0.41 | 0.48 | 0.48 | 0.35 | 0.47 | 0.39 |
| Zhenjiang | 0.19 | 0.20 | 0.21 | 0.21 | 0.36 | 0.22 | 0.21 | 0.22 |
| Hangzhou | 0.59 | 0.61 | 0.60 | 0.59 | 0.60 | 0.62 | 0.61 | 0.61 |
| Ningbo | 0.61 | 0.62 | 0.60 | 0.55 | 0.51 | 0.52 | 0.49 | 0.47 |
| Wenzhou | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.73 |
| Jiaxing | 0.29 | 0.27 | 0.28 | 0.29 | 0.31 | 0.29 | 0.23 | 0.26 |
| Huzhou | 0.31 | 0.21 | 0.21 | 0.22 | 0.29 | 0.24 | 0.20 | 0.24 |
| Shaoxing | 0.40 | 0.40 | 0.42 | 0.43 | 0.39 | 0.35 | 0.35 | 0.35 |
| Jinhua | 0.36 | 0.28 | 0.40 | 0.40 | 0.40 | 0.40 | 0.40 | 0.43 |
| Taizhou | 1.00 | 1.00 | 1.00 | 1.00 | 0.83 | 0.56 | 0.52 | 0.50 |
| Hefei | 0.21 | 0.34 | 0.37 | 0.35 | 0.37 | 0.38 | 0.36 | 0.39 |
| Fuzhou | 0.36 | 0.35 | 0.37 | 0.35 | 0.39 | 0.35 | 0.27 | 0.35 |
| Putian | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Nanchang | 0.37 | 0.24 | 0.28 | 0.42 | 0.54 | 0.41 | 0.28 | 0.27 |
| Jinan | 0.75 | 0.75 | 0.76 | 0.79 | 0.81 | 0.74 | 0.71 | 0.72 |
| Qingdao | 0.95 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Jining | 0.41 | 0.43 | 0.51 | 0.61 | 0.77 | 0.49 | 0.48 | 0.51 |
| Weihai | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.61 | 1.00 | 1.00 |
| Linyi | 0.18 | 0.19 | 0.23 | 0.22 | 0.30 | 0.27 | 0.17 | 0.18 |
| Heze | 0.15 | 0.11 | 0.12 | 0.11 | 0.20 | 0.09 | 0.07 | 0.08 |
| Zhengzhou | 0.25 | 0.25 | 0.25 | 0.26 | 0.24 | 0.29 | 0.28 | 0.29 |
| Luoyang | 0.10 | 0.10 | 0.10 | 0.11 | 0.21 | 0.18 | 0.18 | 0.11 |
| Nanyang | 1.00 | 1.00 | 0.38 | 0.32 | 0.33 | 0.28 | 0.23 | 0.24 |
| Wuhan | 0.70 | 0.71 | 0.69 | 0.71 | 0.74 | 0.70 | 0.63 | 0.71 |
| Yichang | 0.35 | 0.35 | 0.31 | 0.26 | 0.38 | 0.24 | 0.29 | 0.25 |
| Xianning | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Changsha | 0.62 | 0.66 | 0.68 | 0.65 | 0.74 | 0.68 | 0.67 | 0.73 |
| Guangzhou | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Zhuhai | 0.15 | 0.26 | 0.26 | 0.25 | 0.27 | 0.19 | 0.19 | 0.18 |
| Foshan | 0.41 | 0.50 | 0.56 | 0.63 | 1.00 | 1.00 | 1.00 | 1.00 |
| Zhaoqing | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Huizhou | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Zhongshan | 0.22 | 0.25 | 0.28 | 0.27 | 0.37 | 0.29 | 0.38 | 0.38 |
| Nanning | 0.31 | 0.38 | 0.45 | 0.35 | 0.30 | 0.31 | 0.30 | 0.42 |
| Liuzhou | 0.10 | 0.10 | 0.10 | 0.10 | 0.18 | 0.15 | 0.12 | 0.13 |
| Chongqing | 0.37 | 0.36 | 0.35 | 0.29 | 0.30 | 0.30 | 0.28 | 0.28 |
| Guiyang | 0.19 | 0.17 | 0.19 | 0.20 | 0.23 | 0.21 | 0.18 | 0.26 |
| Zunyi | 0.14 | 0.13 | 0.13 | 0.12 | 0.17 | 0.09 | 0.10 | 0.10 |
| Kunming | 0.22 | 0.22 | 0.23 | 0.23 | 0.19 | 0.26 | 0.26 | 0.27 |
| Xi’an | 0.35 | 0.35 | 0.32 | 0.35 | 0.34 | 0.34 | 0.34 | 0.34 |
| Xianyang | 0.15 | 0.09 | 0.08 | 0.08 | 0.19 | 0.12 | 0.09 | 0.08 |
| Yulin | 0.07 | 0.03 | 0.02 | 0.05 | 0.07 | 0.04 | 0.02 | 0.02 |
| Lanzhou | 0.09 | 0.08 | 0.07 | 0.07 | 0.11 | 0.07 | 0.07 | 0.06 |
| Jiayuguan | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Xining | 0.17 | 0.15 | 0.18 | 0.19 | 0.18 | 0.07 | 0.08 | 0.07 |
| Yinchuan | 0.10 | 0.07 | 0.08 | 0.04 | 0.06 | 0.03 | 0.03 | 0.02 |
| Urumqi | 0.11 | 0.08 | 0.07 | 0.06 | 0.12 | 0.05 | 0.04 | 0.05 |

**Table A.2** R1.2

NGMCPI **of 71 cities, 2005-2012**

| Cities | 2005-2006 | 2006-2007 | 2007-2008 | 2008-2009 | 2009-2010 | 2010-2011 | 2011-2012 | Mean |
|---|---|---|---|---|---|---|---|---|
| Beijing | 1.16 | 1.08 | 1.15 | 1.09 | 1.01 | 1.23 | 1.09 | 1.11 |
| Tianjin | 1.10 | 1.10 | 1.13 | 1.08 | 1.07 | 1.05 | 1.10 | 1.09 |
| Shijiazhuang | 0.91 | 0.98 | 1.05 | 1.27 | 1.34 | 1.27 | 1.21 | 1.15 |
| Tangshan | 1.05 | 0.99 | 0.91 | 0.69 | 1.35 | 1.30 | 1.01 | 1.04 |
| Handan | 1.08 | 0.98 | 1.06 | 1.15 | 1.21 | 0.96 | 1.20 | 1.09 |
| Zhangjiakou | 0.86 | 1.10 | 1.09 | 1.10 | 0.97 | 1.00 | 1.02 | 1.02 |
| Taiyuan | 0.97 | 1.07 | 1.07 | 1.25 | 1.21 | 1.14 | 1.23 | 1.13 |
| Jincheng | 0.66 | 0.93 | 0.87 | 0.82 | 1.08 | 1.19 | 1.32 | 0.98 |
| Shuozhou | 0.86 | 0.75 | 0.90 | 1.49 | 0.88 | 0.72 | 1.11 | 0.96 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Yuncheng | 0.80 | 1.06 | 1.48 | 0.69 | 0.77 | 1.19 | 1.05 | 1.01 |
| Hohhot | 0.90 | 0.96 | 0.97 | 1.05 | 1.19 | 1.25 | 1.23 | 1.08 |
| Baotou | 0.96 | 1.06 | 1.96 | 1.55 | 1.28 | 1.32 | 0.79 | 1.27 |
| Shenyang | 1.27 | 1.30 | 0.97 | 1.28 | 1.34 | 0.89 | 1.51 | 1.22 |
| Dalian | 1.02 | 0.97 | 1.28 | 1.17 | 1.25 | 1.21 | 1.15 | 1.15 |
| Changchun | 1.12 | 1.17 | 1.24 | 1.02 | 1.23 | 1.33 | 1.08 | 1.17 |
| Jilin | 0.93 | 2.23 | 1.24 | 1.46 | 1.25 | 1.14 | 1.25 | 1.36 |
| Siping | 0.71 | 0.97 | 0.87 | 0.97 | 0.96 | 1.01 | 1.04 | 0.93 |
| Harbin | 1.17 | 1.10 | 1.11 | 1.00 | 1.11 | 0.96 | 1.08 | 1.08 |
| Shanghai | 1.14 | 1.15 | 1.11 | 1.11 | 1.28 | 0.89 | 1.13 | 1.12 |
| Nanjing | 0.96 | 1.19 | 1.16 | 1.14 | 0.99 | 1.18 | 1.16 | 1.11 |
| Wuxi | 0.40 | 1.21 | 1.12 | 1.09 | 1.16 | 1.13 | 1.11 | 1.03 |
| Changzhou | 1.17 | 1.32 | 1.23 | 1.18 | 1.20 | 0.90 | 1.06 | 1.15 |
| Suzhou | 1.07 | 1.14 | 1.12 | 1.02 | 1.13 | 1.11 | 1.00 | 1.08 |
| Nantong | 0.95 | 1.34 | 1.18 | 1.27 | 1.00 | 1.11 | 1.47 | 1.19 |
| Yancheng | 0.50 | 0.96 | 1.03 | 1.14 | 0.72 | 1.52 | 1.28 | 1.02 |
| Zhenjiang | 0.94 | 1.04 | 1.03 | 1.09 | 1.31 | 1.18 | 1.19 | 1.11 |
| Hangzhou | 1.16 | 1.07 | 1.14 | 1.01 | 1.19 | 1.17 | 1.12 | 1.12 |
| Ningbo | 1.21 | 1.02 | 1.06 | 0.88 | 1.33 | 1.11 | 1.03 | 1.09 |
| Wenzhou | 0.98 | 1.02 | 1.00 | 0.93 | 1.08 | 0.89 | 0.74 | 0.95 |
| Jiaxing | 0.86 | 1.29 | 1.32 | 1.21 | 1.24 | 0.94 | 1.10 | 1.14 |
| Huzhou | 0.96 | 0.98 | 1.04 | 1.02 | 1.14 | 1.26 | 1.27 | 1.10 |
| Shaoxing | 1.24 | 1.20 | 1.22 | 1.17 | 1.15 | 1.01 | 1.12 | 1.16 |
| Jinhua | 0.91 | 1.01 | 1.17 | 1.17 | 1.29 | 1.18 | 1.11 | 1.12 |
| Taizhou | 1.00 | 0.64 | 0.74 | 0.85 | 1.21 | 1.02 | 1.01 | 0.92 |
| Hefei | 0.96 | 1.40 | 1.41 | 1.04 | 1.04 | 1.14 | 1.20 | 1.17 |
| Fuzhou | 0.94 | 1.04 | 0.98 | 0.95 | 1.09 | 1.13 | 1.18 | 1.04 |
| Putian | 1.00 | 0.94 | 1.06 | 0.55 | 1.31 | 0.69 | 1.02 | 0.94 |
| Nanchang | 0.64 | 0.92 | 1.05 | 1.16 | 1.16 | 0.69 | 1.34 | 1.00 |
| Jinan | 1.02 | 1.18 | 1.12 | 1.03 | 1.05 | 1.04 | 1.01 | 1.06 |
| Qingdao | 1.14 | 1.22 | 1.10 | 1.00 | 1.09 | 1.16 | 1.04 | 1.11 |
| Jining | 1.05 | 1.50 | 1.25 | 1.08 | 1.00 | 1.09 | 1.31 | 1.19 |
| Weihai | 0.35 | 0.86 | 1.26 | 1.34 | 1.29 | 0.93 | 1.24 | 1.04 |
| Linyi | 1.04 | 1.25 | 1.06 | 0.87 | 1.41 | 1.24 | 0.63 | 1.07 |
| Heze | 0.71 | 0.88 | 1.00 | 0.82 | 0.89 | 1.07 | 1.04 | 0.92 |
| Zhengzhou | 0.97 | 0.85 | 1.31 | 1.24 | 1.17 | 1.16 | 1.15 | 1.12 |
| Luoyang | 0.94 | 0.97 | 1.90 | 1.48 | 1.30 | 1.23 | 1.16 | 1.29 |
| Nanyang | 0.55 | 0.60 | 0.51 | 0.94 | 1.19 | 1.15 | 1.15 | 0.87 |
| Wuhan | 0.91 | 1.08 | 1.29 | 1.21 | 1.13 | 1.10 | 1.27 | 1.14 |
| Yichang | 1.07 | 1.14 | 1.17 | 1.24 | 1.19 | 1.03 | 0.98 | 1.12 |
| Xianning | 0.83 | 0.85 | 0.72 | 0.62 | 1.12 | 0.69 | 1.21 | 0.86 |
| Changsha | 0.95 | 0.99 | 0.84 | 1.38 | 1.31 | 1.25 | 1.30 | 1.15 |
| Guangzhou | 1.20 | 1.26 | 1.28 | 1.16 | 1.16 | 1.00 | 1.00 | 1.15 |
| Zhuhai | 1.04 | 1.02 | 0.99 | 0.99 | 1.04 | 1.03 | 1.03 | 1.02 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Foshan | 1.52 | 1.45 | 1.33 | 1.42 | 1.41 | 0.91 | 1.01 | 1.29 |
| Zhaoqing | 1.00 | 1.00 | 1.00 | 0.75 | 1.33 | 1.00 | 1.00 | 1.01 |
| Huizhou | 1.00 | 1.00 | 1.00 | 0.93 | 1.07 | 1.00 | 1.00 | 1.00 |
| Zhongshan | 0.89 | 1.15 | 1.07 | 1.00 | 1.08 | 1.10 | 0.99 | 1.04 |
| Nanning | 1.02 | 1.15 | 1.02 | 1.01 | 0.72 | 1.00 | 1.56 | 1.07 |
| Liuzhou | 0.94 | 0.97 | 0.97 | 0.92 | 0.95 | 1.20 | 1.32 | 1.04 |
| Chongqing | 1.09 | 1.11 | 0.93 | 1.13 | 1.13 | 1.02 | 1.10 | 1.07 |
| Guiyang | 0.98 | 1.04 | 1.02 | 1.01 | 1.21 | 1.33 | 1.45 | 1.15 |
| Zunyi | 0.90 | 0.93 | 0.94 | 0.97 | 0.96 | 1.49 | 1.20 | 1.06 |
| Kunming | 0.98 | 1.08 | 1.30 | 1.28 | 1.27 | 1.21 | 1.18 | 1.19 |
| Xi’an | 0.83 | 0.83 | 1.66 | 1.36 | 0.79 | 1.42 | 1.23 | 1.16 |
| Xianyang | 0.90 | 0.84 | 0.92 | 0.91 | 1.33 | 1.65 | 1.25 | 1.11 |
| Yulin | 0.98 | 1.01 | 1.05 | 0.63 | 1.14 | 1.23 | 1.19 | 1.03 |
| Lanzhou | 1.00 | 1.00 | 0.99 | 0.99 | 1.10 | 1.67 | 1.48 | 1.18 |
| Jiayuguan | 1.00 | 0.89 | 1.12 | 0.58 | 0.59 | 0.44 | 0.34 | 0.71 |
| Xining | 0.99 | 0.80 | 0.90 | 0.93 | 0.85 | 1.20 | 0.88 | 0.93 |
| Yinchuan | 0.92 | 1.46 | 0.45 | 0.76 | 0.89 | 1.14 | 1.52 | 1.02 |
| Urumqi | 0.57 | 0.97 | 0.94 | 1.03 | 0.93 | 1.10 | 1.70 | 1.03 |
| Mean | 0.96 | 1.07 | 1.10 | 1.06 | 1.12 | 1.11 | 1.14 | 1.08 |

**Table A.3** R1.2

EC **of 71 cities, 2005-2012**

| **Cities** | **2005-2006** | **2006-2007** | **2007-2008** | **2008-2009** | **2009-2010** | **2010-2011** | **2011-2012** | **Mean** |
|---|---|---|---|---|---|---|---|---|
| Beijing | 1.00 | 0.98 | 1.03 | 1.04 | 0.98 | 1.06 | 0.95 | 1.01 |
| Tianjin | 1.00 | 0.97 | 1.00 | 0.98 | 0.99 | 0.95 | 1.01 | 0.99 |
| Shijiazhuang | 0.90 | 1.34 | 0.98 | 1.02 | 0.89 | 1.12 | 1.00 | 1.03 |
| Tangshan | 1.00 | 1.00 | 1.00 | 0.86 | 0.84 | 1.38 | 0.84 | 0.99 |
| Handan | 1.15 | 1.09 | 0.99 | 1.35 | 0.81 | 0.97 | 0.87 | 1.03 |
| Zhangjiakou | 1.01 | 0.97 | 0.96 | 1.57 | 0.58 | 0.96 | 0.94 | 1.00 |
| Taiyuan | 1.33 | 1.04 | 0.94 | 0.99 | 1.01 | 0.93 | 1.04 | 1.04 |
| Jincheng | 0.60 | 1.17 | 0.91 | 1.71 | 0.44 | 0.89 | 1.01 | 0.96 |
| Shuozhou | 1.00 | 0.86 | 0.79 | 1.83 | 0.34 | 1.00 | 0.99 | 0.97 |
| Yuncheng | 0.41 | 0.97 | 0.99 | 1.33 | 0.87 | 0.58 | 0.99 | 0.88 |
| Hohhot | 1.11 | 1.09 | 1.01 | 1.63 | 0.94 | 0.71 | 1.01 | 1.07 |
| Baotou | 0.97 | 1.11 | 1.11 | 1.91 | 0.95 | 0.66 | 1.01 | 1.10 |
| Shenyang | 1.16 | 1.17 | 1.30 | 1.02 | 0.93 | 0.77 | 1.56 | 1.13 |
| Dalian | 1.09 | 0.99 | 1.04 | 1.04 | 1.05 | 1.00 | 1.02 | 1.03 |
| Changchun | 1.18 | 1.05 | 1.04 | 1.21 | 0.98 | 0.89 | 1.09 | 1.06 |
| Jilin | 1.03 | 1.02 | 1.32 | 1.99 | 0.80 | 0.48 | 1.25 | 1.13 |
| Siping | 0.91 | 1.31 | 0.68 | 1.81 | 0.39 | 1.01 | 1.08 | 1.03 |
| Harbin | 1.02 | 1.04 | 1.01 | 0.93 | 0.95 | 0.95 | 1.01 | 0.99 |
| Shanghai | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Nanjing | 1.06 | 1.00 | 1.00 | 0.96 | 0.99 | 1.00 | 0.97 | 1.00 |
| Wuxi | 0.44 | 2.26 | 0.40 | 1.04 | 0.98 | 0.85 | 1.16 | 1.02 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Changzhou | 1.00 | 1.02 | 0.92 | 1.00 | 0.92 | 1.03 | 0.95 | 0.98 |
| Suzhou | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Nantong | 0.99 | 1.04 | 0.97 | 1.23 | 0.85 | 0.81 | 1.31 | 1.03 |
| Yancheng | 0.85 | 0.93 | 1.17 | 0.99 | 0.74 | 1.35 | 0.83 | 0.98 |
| Zhenjiang | 1.02 | 1.08 | 0.97 | 1.76 | 0.61 | 0.96 | 1.01 | 1.06 |
| Hangzhou | 1.02 | 0.99 | 0.99 | 1.02 | 1.02 | 0.98 | 1.00 | 1.00 |
| Ningbo | 1.02 | 0.96 | 0.92 | 0.93 | 1.03 | 0.95 | 0.95 | 0.96 |
| Wenzhou | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.73 | 0.96 |
| Jiaxing | 0.93 | 1.05 | 1.04 | 1.05 | 0.96 | 0.78 | 1.11 | 0.99 |
| Huzhou | 0.67 | 0.97 | 1.08 | 1.33 | 0.81 | 0.86 | 1.17 | 0.98 |
| Shaoxing | 0.99 | 1.06 | 1.02 | 0.90 | 0.91 | 0.99 | 1.00 | 0.98 |
| Jinhua | 0.77 | 1.46 | 0.99 | 1.00 | 1.00 | 0.99 | 1.09 | 1.04 |
| Taizhou | 1.00 | 1.00 | 1.00 | 0.83 | 0.68 | 0.93 | 0.96 | 0.91 |
| Hefei | 1.59 | 1.09 | 0.95 | 1.05 | 1.04 | 0.95 | 1.07 | 1.11 |
| Fuzhou | 0.96 | 1.06 | 0.93 | 1.13 | 0.88 | 0.78 | 1.31 | 1.01 |
| Putian | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Nanchang | 0.66 | 1.14 | 1.50 | 1.29 | 0.77 | 0.67 | 0.99 | 1.00 |
| Jinan | 1.00 | 1.02 | 1.04 | 1.02 | 0.92 | 0.96 | 1.02 | 1.00 |
| Qingdao | 1.06 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.01 |
| Jining | 1.07 | 1.18 | 1.20 | 1.26 | 0.63 | 0.99 | 1.05 | 1.05 |
| Weihai | 1.00 | 1.00 | 1.00 | 1.00 | 0.61 | 1.64 | 1.00 | 1.04 |
| Linyi | 1.04 | 1.20 | 0.96 | 1.40 | 0.89 | 0.64 | 1.03 | 1.02 |
| Heze | 0.73 | 1.04 | 0.98 | 1.79 | 0.43 | 0.83 | 1.03 | 0.98 |
| Zhengzhou | 0.98 | 0.99 | 1.07 | 0.90 | 1.22 | 0.98 | 1.02 | 1.02 |
| Luoyang | 1.02 | 1.05 | 1.05 | 1.90 | 0.87 | 0.96 | 0.64 | 1.07 |
| Nanyang | 1.00 | 0.38 | 0.85 | 1.04 | 0.84 | 0.81 | 1.09 | 0.86 |
| Wuhan | 1.01 | 0.97 | 1.04 | 1.04 | 0.94 | 0.91 | 1.12 | 1.00 |
| Yichang | 0.99 | 0.90 | 0.84 | 1.46 | 0.62 | 1.23 | 0.85 | 0.99 |
| Xianning | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Changsha | 1.07 | 1.03 | 0.96 | 1.13 | 0.92 | 0.98 | 1.09 | 1.03 |
| Guangzhou | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Zhuhai | 1.70 | 1.00 | 0.95 | 1.09 | 0.72 | 0.98 | 0.97 | 1.06 |
| Foshan | 1.24 | 1.11 | 1.13 | 1.58 | 1.00 | 1.00 | 1.00 | 1.15 |
| Zhaoqing | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Huizhou | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Zhongshan | 1.13 | 1.15 | 0.94 | 1.40 | 0.78 | 1.31 | 1.00 | 1.10 |
| Nanning | 1.21 | 1.19 | 0.79 | 0.83 | 1.05 | 0.96 | 1.42 | 1.07 |
| Liuzhou | 0.97 | 0.97 | 1.02 | 1.81 | 0.81 | 0.82 | 1.07 | 1.07 |
| Chongqing | 0.97 | 0.98 | 0.82 | 1.05 | 1.00 | 0.92 | 1.02 | 0.96 |
| Guiyang | 0.88 | 1.10 | 1.05 | 1.16 | 0.90 | 0.88 | 1.44 | 1.06 |
| Zunyi | 0.90 | 0.99 | 0.96 | 1.37 | 0.55 | 1.03 | 1.05 | 0.98 |
| Kunming | 1.01 | 1.02 | 1.03 | 0.80 | 1.38 | 1.02 | 1.04 | 1.04 |
| Xi’an | 1.01 | 0.90 | 1.12 | 0.96 | 1.00 | 1.01 | 0.99 | 1.00 |
| Xianyang | 0.58 | 0.86 | 1.02 | 2.41 | 0.61 | 0.77 | 0.92 | 1.02 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Yulin | 0.39 | 0.73 | 2.33 | 1.51 | 0.55 | 0.56 | 1.02 | 1.01 |
| Lanzhou | 0.84 | 0.96 | 1.00 | 1.48 | 0.66 | 1.02 | 0.87 | 0.98 |
| Jiayuguan | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Xining | 0.87 | 1.27 | 1.02 | 0.97 | 0.37 | 1.12 | 0.94 | 0.94 |
| Yinchuan | 0.65 | 1.19 | 0.52 | 1.42 | 0.45 | 0.95 | 0.99 | 0.88 |
| Urumqi | 0.72 | 0.88 | 0.89 | 1.87 | 0.43 | 0.87 | 1.06 | 0.96 |
| Mean | 0.97 | 1.05 | 1.01 | 1.23 | 0.85 | 0.95 | 1.03 | 1.01 |

**Table A.4** R1.2

TC **of 71 cities, 2005-2012**

| Cities | 2005-2006 | 2006-2007 | 2007-2008 | 2008-2009 | 2009-2010 | 2010-2011 | 2011-2012 | Mean |
|---|---|---|---|---|---|---|---|---|
| Beijing | 1.16 | 1.10 | 1.11 | 1.05 | 1.03 | 1.16 | 1.14 | 1.11 |
| Tianjin | 1.10 | 1.13 | 1.12 | 1.11 | 1.09 | 1.11 | 1.09 | 1.11 |
| Shijiazhuang | 1.02 | 0.73 | 1.06 | 1.25 | 1.51 | 1.13 | 1.21 | 1.13 |
| Tangshan | 1.05 | 0.99 | 0.91 | 0.81 | 1.61 | 0.94 | 1.21 | 1.07 |
| Handan | 0.94 | 0.90 | 1.07 | 0.86 | 1.49 | 0.99 | 1.39 | 1.09 |
| Zhangjiakou | 0.85 | 1.14 | 1.13 | 0.70 | 1.67 | 1.05 | 1.08 | 1.09 |
| Taiyuan | 0.73 | 1.03 | 1.13 | 1.26 | 1.19 | 1.22 | 1.19 | 1.11 |
| Jincheng | 1.09 | 0.80 | 0.96 | 0.48 | 2.44 | 1.33 | 1.30 | 1.20 |
| Shuozhou | 0.86 | 0.87 | 1.14 | 0.82 | 2.59 | 0.72 | 1.12 | 1.16 |
| Yuncheng | 1.94 | 1.09 | 1.49 | 0.52 | 0.89 | 2.04 | 1.07 | 1.29 |
| Hohhot | 0.81 | 0.88 | 0.96 | 0.64 | 1.27 | 1.75 | 1.21 | 1.08 |
| Baotou | 0.98 | 0.96 | 1.77 | 0.81 | 1.35 | 2.00 | 0.78 | 1.24 |
| Shenyang | 1.09 | 1.12 | 0.75 | 1.25 | 1.43 | 1.16 | 0.97 | 1.11 |
| Dalian | 0.94 | 0.98 | 1.24 | 1.13 | 1.19 | 1.21 | 1.13 | 1.12 |
| Changchun | 0.96 | 1.11 | 1.19 | 0.84 | 1.26 | 1.50 | 0.99 | 1.12 |
| Jilin | 0.90 | 2.18 | 0.93 | 0.73 | 1.56 | 2.39 | 1.00 | 1.39 |
| Siping | 0.79 | 0.74 | 1.28 | 0.53 | 2.45 | 1.00 | 0.96 | 1.11 |
| Harbin | 1.15 | 1.06 | 1.10 | 1.09 | 1.17 | 1.01 | 1.07 | 1.09 |
| Shanghai | 1.14 | 1.15 | 1.11 | 1.11 | 1.28 | 0.89 | 1.13 | 1.12 |
| Nanjing | 0.90 | 1.19 | 1.16 | 1.19 | 1.00 | 1.18 | 1.19 | 1.12 |
| Wuxi | 0.90 | 0.53 | 2.81 | 1.05 | 1.18 | 1.32 | 0.95 | 1.25 |
| Changzhou | 1.17 | 1.29 | 1.33 | 1.18 | 1.31 | 0.87 | 1.12 | 1.18 |
| Suzhou | 1.07 | 1.14 | 1.12 | 1.02 | 1.13 | 1.11 | 1.00 | 1.08 |
| Nantong | 0.95 | 1.29 | 1.22 | 1.04 | 1.17 | 1.37 | 1.12 | 1.17 |
| Yancheng | 0.59 | 1.03 | 0.88 | 1.15 | 0.98 | 1.13 | 1.54 | 1.04 |
| Zhenjiang | 0.92 | 0.96 | 1.05 | 0.62 | 2.14 | 1.23 | 1.18 | 1.16 |
| Hangzhou | 1.13 | 1.08 | 1.15 | 0.99 | 1.16 | 1.19 | 1.12 | 1.12 |
| Ningbo | 1.18 | 1.06 | 1.16 | 0.95 | 1.30 | 1.17 | 1.09 | 1.13 |
| Wenzhou | 0.98 | 1.02 | 1.00 | 0.93 | 1.08 | 0.89 | 1.02 | 0.99 |
| Jiaxing | 0.92 | 1.24 | 1.26 | 1.15 | 1.30 | 1.21 | 0.99 | 1.15 |
| Huzhou | 1.42 | 1.01 | 0.97 | 0.77 | 1.41 | 1.47 | 1.09 | 1.16 |
| Shaoxing | 1.25 | 1.13 | 1.20 | 1.30 | 1.27 | 1.02 | 1.12 | 1.18 |
| Jinhua | 1.19 | 0.69 | 1.18 | 1.17 | 1.30 | 1.19 | 1.01 | 1.10 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Taizhou | 1.00 | 0.64 | 0.74 | 1.02 | 1.78 | 1.10 | 1.05 | 1.05 |
| Hefei | 0.60 | 1.29 | 1.48 | 1.00 | 1.01 | 1.20 | 1.12 | 1.10 |
| Fuzhou | 0.97 | 0.98 | 1.06 | 0.84 | 1.23 | 1.45 | 0.90 | 1.06 |
| Putian | 1.00 | 0.94 | 1.06 | 0.55 | 1.31 | 0.69 | 1.02 | 0.94 |
| Nanchang | 0.97 | 0.81 | 0.70 | 0.90 | 1.52 | 1.03 | 1.36 | 1.04 |
| Jinan | 1.02 | 1.16 | 1.08 | 1.01 | 1.14 | 1.09 | 0.99 | 1.07 |
| Qingdao | 1.08 | 1.22 | 1.10 | 1.00 | 1.09 | 1.16 | 1.04 | 1.10 |
| Jining | 0.99 | 1.28 | 1.04 | 0.86 | 1.58 | 1.11 | 1.25 | 1.16 |
| Weihai | 0.35 | 0.86 | 1.26 | 1.34 | 2.12 | 0.57 | 1.24 | 1.10 |
| Linyi | 1.00 | 1.04 | 1.10 | 0.62 | 1.60 | 1.93 | 0.61 | 1.13 |
| Heze | 0.96 | 0.85 | 1.02 | 0.46 | 2.05 | 1.29 | 1.01 | 1.09 |
| Zhengzhou | 0.99 | 0.86 | 1.23 | 1.38 | 0.96 | 1.18 | 1.12 | 1.10 |
| Luoyang | 0.92 | 0.92 | 1.81 | 0.78 | 1.49 | 1.28 | 1.82 | 1.29 |
| Nanyang | 0.55 | 1.60 | 0.60 | 0.90 | 1.41 | 1.42 | 1.06 | 1.08 |
| Wuhan | 0.91 | 1.12 | 1.25 | 1.16 | 1.19 | 1.21 | 1.13 | 1.14 |
| Yichang | 1.08 | 1.27 | 1.40 | 0.85 | 1.90 | 0.84 | 1.14 | 1.21 |
| Xianning | 0.83 | 0.85 | 0.72 | 0.62 | 1.12 | 0.69 | 1.21 | 0.86 |
| Changsha | 0.89 | 0.95 | 0.88 | 1.22 | 1.42 | 1.28 | 1.19 | 1.12 |
| Guangzhou | 1.20 | 1.26 | 1.28 | 1.16 | 1.16 | 1.00 | 1.00 | 1.15 |
| Zhuhai | 0.61 | 1.03 | 1.05 | 0.90 | 1.45 | 1.05 | 1.06 | 1.02 |
| Foshan | 1.22 | 1.31 | 1.17 | 0.90 | 1.41 | 0.91 | 1.01 | 1.13 |
| Zhaoqing | 1.00 | 1.00 | 1.00 | 0.75 | 1.33 | 1.00 | 1.00 | 1.01 |
| Huizhou | 1.00 | 1.00 | 1.00 | 0.93 | 1.07 | 1.00 | 1.00 | 1.00 |
| Zhongshan | 0.79 | 1.00 | 1.14 | 0.71 | 1.39 | 0.84 | 0.99 | 0.98 |
| Nanning | 0.85 | 0.97 | 1.28 | 1.21 | 0.68 | 1.04 | 1.09 | 1.02 |
| Liuzhou | 0.97 | 1.00 | 0.95 | 0.51 | 1.17 | 1.45 | 1.24 | 1.04 |
| Chongqing | 1.13 | 1.12 | 1.14 | 1.07 | 1.14 | 1.11 | 1.09 | 1.11 |
| Guiyang | 1.12 | 0.95 | 0.97 | 0.87 | 1.34 | 1.51 | 1.01 | 1.11 |
| Zunyi | 1.00 | 0.95 | 0.98 | 0.71 | 1.74 | 1.45 | 1.14 | 1.14 |
| Kunming | 0.97 | 1.06 | 1.27 | 1.60 | 0.92 | 1.18 | 1.14 | 1.16 |
| Xi’an | 0.82 | 0.92 | 1.49 | 1.41 | 0.79 | 1.41 | 1.25 | 1.16 |
| Xianyang | 1.55 | 0.98 | 0.90 | 0.38 | 2.18 | 2.14 | 1.36 | 1.36 |
| Yulin | 2.50 | 1.37 | 0.45 | 0.42 | 2.09 | 2.22 | 1.17 | 1.46 |
| Lanzhou | 1.18 | 1.04 | 0.99 | 0.67 | 1.66 | 1.64 | 1.71 | 1.27 |
| Jiayuguan | 1.00 | 0.89 | 1.12 | 0.58 | 0.59 | 0.44 | 0.34 | 0.71 |
| Xining | 1.14 | 0.63 | 0.88 | 0.95 | 2.29 | 1.07 | 0.93 | 1.13 |
| Yinchuan | 1.41 | 1.23 | 0.85 | 0.54 | 2.00 | 1.20 | 1.53 | 1.25 |
| Urumqi | 0.80 | 1.10 | 1.06 | 0.55 | 2.16 | 1.26 | 1.60 | 1.22 |
| Mean | 1.02 | 1.04 | 1.12 | 0.91 | 1.42 | 1.22 | 1.12 | 1.12 |