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# Will Low-Carbon Economy Promote Employment or Not: An Empirical Study Based on 1998-2010 Provincial Panel Data in China

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## Abstract

Sampling on China's provincial panel data from 1998 to 2010, this paper constructs China's Cumulative Malmquist Carbon Dioxide Emission Performance Index (CMCPI) as a proxy variable to measure its development of low-carbon economy. System GMM estimation method is applied to explore the relationship between CMCPI and the employment in China, including the total employment and the employment structure in energy-intensive and low-power industries. The main three conclusions are as follows: (a) China's $CO_2$ Emission Performance is highest in Eastern China and lowest in Central China; (b) the provincial differences of MCPI is mainly due to the provincial technology changes rather than efficiency changes; (c) higher carbon dioxide emission performance significantly promotes the employment of low-power industries and the total employment, but it seems to impede the employment of energy-intensive industries in Eastern China. It is found that higher CMCPI would increase the total employment and improve the employment structure in Eastern China, while that doesn't happen in Central and Western China.

**Key words:** CMCPI; Total employment; Employment structure

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## INTRODUCTION

The definition of Low-carbon Economy was first introduced by British government in its energy white paper 2003, entitled *Our Energy Future: Creating a Low Carbon Economy*[1]. The white paper says that a low-carbon economy is more productive with much less natural resources consumption and environmental pollution and creates more opportunity for business and employment. Zhuang (2005) believes that the essence of low-carbon economy is energy efficiency and clean energy structure; the core is the innovation of energy technology and institution and the goal is to establish a new economic mode which can reduce the $CO_2$ emission to promote the sustainable relationship between society and nature. Nicholas Stem (2006) discusses in detail on the economic effects caused by climate changes and the costs and payoffs of greenhouse gas emission in the report *Stern Review: The Economics of Climate Change*. The report emphasizes the necessity that every government promptly takes effective action to reduce greenhouse gas emission to avoid a possibly worsen effects on economic growth and social development caused by climate change.

Since the reform and opening up was carried out in 1978，China has achieved rapid economic growth for more than 30 years. However, it is at the expense of destroying the environment to some extent. China's existing issue on the economic development model which

1 UK Energy White Paper: Our energy future- creating a low carbon economy, 2003

is featured with energy-intensive, high pollution and low efficiency has not radically changed. China consumed roughly 3.25 billion tons of standard coal in 2011. In 2011, China consumed 1.71billion total coal of oil equivalent, accounting for 48.2 percentage of the world coal consumption, 428.6 million tons of oil becoming the second largest oil importer and consumer after the United States in the world and 109 billion cubic meters of gas, surpassing Japan as the fourth largest gas consumer after the United States, Russia and Iran. According to British Petroleum Co. Ltd., China consumed 11.2% more energy in 2010 than that in 2009 and became the largest energy consumer in the world surpassing the United States. In recent years, China has improved its power usage efficiency, but there is still a wide gap compared with developed countries. Measured by exchange rate method, China's energy consumptions per GDP was 2.65 times as much as the US, 4.51 times as Japan, 4.39 times as German and 2.17 times as the world average. Even measured by PPP method, it was still 1.54 times as much as the US, 2.07 times as Japan, 2.21 times as German and 1.49 times as the world average.

Although there are controversies in how to calculate $CO_2$ emissions among different countries, the majority of researches argue that China lets out more than 6 billion tons of $CO_2$ each recent year on average and becomes the largest $CO_2$ emitter in the world, about one fifth of the world's total emissions[2] and that China is confronted with increasing pressure to reduce its emissions[3]. Moreover, it's quite critical for China's development mode which brings issues such as energy shortage, resources waste and environmental pollution, so China is under more internal pressure to reform its economic development mode. In these settings, more and more appeals are made to develop low-carbon economy at home and abroad.

However, the studies on what effects would low-carbon economy has on employment get quite different or even contradictory conclusions, even though quite a few studies suggest that low-carbon economy could promote employment. This paper reviews the literature on the relationship between low-carbon economy and employment firstly, and finds a proxy, i.e., Cumulative Malmquist Carbon Dioxide Emission Performance Index (CMCPI), to measure the development of low-carbon economy, and then classifies employment into employment scale and employment structure divided by energy consumption industries. We start our study with how CMCPI would affect the employments in industries with different levels of energy consumptions, analyze the correlations between CMCPI and the employment scale or employment structure and further discuss the issue among different regions of China. The remaining structure of this paper is established as follows: section two is literature review; section three is the measurement of CMCPI; section four is theoretical model and data; section five is empirical analysis; and section six is conclusion.

## 1. LITERATURE REVIEW

There is relatively less literature on the relationship between low-carbon economy and employment, most of which indirectly discusses it by studying how low-carbon economy affects economic growth. Academia hasn't reached a consensus on whether low-carbon economy would promote employment or not.[4]

Some scholars argue that low-carbon economy would worsen employment. Babiker and Eckaus (2007) examine the possible employment effects of limiting greenhouse gas emissions and believe that it would cause unemployment for the US to limit the greenhouse gas without other compensating measures due to the imperfect labor market, labor liquidity and the rigidity of wage adjustment in the short run, and that the limitation in the US would decrease its GDP by 4%. Pempetzoglou and Karagianni (2008) use CGE Model to study the economic effects of energy tax in Greece and find that energy tax would decrease its output and employment especially in energy-intensive industries such as power and oil sectors since the tax increases the price of energy products and reduces the demand on energy products. For China, Thampapillai et al. (2007) decompose China's economic growth into environment and resource factors and find that China doesn't achieve so rapid economic growth as it seems to do. They further estimate that China's unemployment rate would be as high as 32% if it obeyed sustainable development rule. Wang et al. (2005) applies a recursive dynamic CGE model encompassing economic, energetic and environmental systems to analyze the economic effects of China's $CO_2$ mitigation policy, and finds that the reduction policy would improve the energy usage efficiency but would bring negative effects to the economic growth and employment. Lin et al. (2010) applies a similar model to Wang's to measure what effects the optimal energy structure has on macroeconomics with the constraints of energy saving and mitigation. They argue that on one hand $CO_2$ mitigation helps China to use more renewable energy and to improve its energy consumption structure, but on the other hand it greatly

[2] According to Carbon Dioxide Information Analysis Center of the United States Energy Department, the global $CO_2$ emissions are 33.5 billion tons in 2010, increasing by 5.9% relative to 2009.

[3] Fu et al (2008) emphasize the urgency to develop low-carbon economy in China, based their analysis on China's greenhouse reduction pressure, energy security and resource environment.

[4] Most studies argue that the negative employment effect of low-carbon economy mainly happens in high energy consumption industries, e.g., oil refining industry (Pempetzoglou et al., 2008), coal-fired power plant (Pan et al., 2009). Some studies suggest that low-carbon economy also has a negative effect on total employment (Babiker & Eckaus, 2007; Lin et al., 2010).

increases China's energy costs which bring big shocks to its real economy. That is to say, even if developing renewable energy would increase employment to some degree, the raised energetic costs would bring greater negative shocks to output and employment in other industries.

Some argue that the industry chain of low-carbon economy should gradually go into maturity with the improvement of industry structure, though low-carbon economy would easily decrease total employment because of the structural unemployment in the short run (Tan, 2010). Fankhauser et al. (2008) analyzes the employment effect of climate policies and believes that the outcomes would change in different time spans. In the short run, a climate policy transfers employment from high-carbon fields to low-carbon ones, and the net employment effect would be positive because low-carbon sectors are more labor-intensive. In the long run, the climate policy would bring a new round of creative destruction and create more opportunity of employment and economic growth after the whole economic structure is adjusted. Hewett and Foley (2000), Bezdek et al. (2008), Markandya and Ortiz (2008) support the above conclusion after inspecting England, the US and Czech, respectively. Morgenstern et al. (2001) inspect whether environmental policies will affect controlled industries by using data collected from paper making, plastic manufacturing, oil refining and steel industry. They decompose the link between environmental regulation and employment into three distinct components: factor shifts to more or less labor intensity, changes in total expenditures, and changes in the quantity of output demanded and find that the increasing expenditures on environmental protection have not changed the employment with industry, which is because the investment on environmental protection is more demand inelastic for environmental activities are more labor-intensive than general production activities. Yang and Tian (2010) estimate the energy input employment elasticity of China's 7 industries and believe that the energy saving and mitigation policy would decrease employment particularly in industrial department in short term, but it would increase employment particularly in agricultural and service department in long term.

Besides above research, some scholars find that it's possible to get a win-win outcome between $CO_2$ mitigation and economic output growth or employment if the collected carbon taxes or energy taxes were appropriately used to offset the distorted allocation of income taxes or social insurance expenditure. Crowley (1999), Palatnik and Shechter (2010) study on Europe and Israel and confirm that environmental protection is not an economic burden but an opportunity to increase employment and helps to generate the "double dividend"[5].

[5] However, the double dividend couldn't be realized through fair and foul. Babiker, Metcalf and Reilly(2003)use multinational data to analyze the effect of mitigation policy and find that the policy to reduce global carbon emissions could not bring double dividend.

Beyond the two arguments of employment impediment and employment promotion, some hold that low-carbon economy doesn't significantly affect employment or at least the influence is negligible (Matthew & Elliott, 2007; Andersen, 2010).

The related literature implies that low-carbon economy affects employment mainly by the path of low-carbon economy changing the employment structure in different energy-intensive industries. The critics hold the opinion that low-carbon economy would cause a sharp decrease in employment in highly energy-intensive departments and finally worsen the total employment. The supporters insist that low-carbon economy would possibly improve the total employment by the increasing the employment in less energy-intensive departments if enough measures were taken to offset the negative employment effects on highly energy-intensive departments.

What should we pay attention is that there are some limitations in the literature reviewed. For the analytical method, most of them focus on theoretical logic analysis or CGE model, which has a weakness on dynamically analyzing and comparing the degree of low-carbon economy's employment effect. Moreover, CGE analysis usually comes to a conclusion of bias and errors without allowing for technology factor. Quantitative analysis will make up for the mentioned weakness to a large degree. From the aspect of the analyzed object, we can easily find that there are significant economic heterogeneities among different areas in China, so the research based on the whole nation will even up such differences and draw a wrong conclusion.

By now, studies on the employment effect of low-carbon economy in China's separate regions are relatively few. But as a matter of fact, it's very necessary to pay more attention on whether low-carbon economy among different regions in China would cause significantly different effects on employment because China's regional development level differences are objectively there[6]. As every province in China has its own leading industries and the stages of development are different in Eastern China, Central China and Western China, we'd like to explore the optimal path on which low-carbon economy is related to employment among different regions in China. In this paper, quantitative analysis is used to study on how low-carbon economy affects employment among different regions in China, and the industries of all regions

[6] According to Blue Book of China's industrialization published by Chinese Academy of Social Sciences in 2007, the industrialization composite index of Eastern China was 78 in 2005, in the first half of the late stage of industrialization; Northeastern China's index was 45, in the first half of the middle stage of industrialization; Central and Western China's indexes are 30 and 25, respectively, both in the second half of the early stage of industrialization. In Eastern China, the Yangtze River Delta, Pearl River Delta had the industrialization composite index of 85 and 80, respectively, both in the second half of the late stage of industrialization; Bo Hai Coastal Region's index was 70, in the first half of the late stage of industrialization.

are classified into two categories, i.e., energy-intensive industries and low-power industries.

## 2. CHINA'S CUMULATIVE MALMQUIST CARBON DIOXIDE EMISSION PERFORMANCE INDEX

Reviewing the related literature we can find that the main indexes usually used to measure carbon dioxide emission performance are Carbon Dioxide Emission per Energy Consumption, Energy Consumptions per GDP, Carbon Dioxide Emission per GDP and Per Capita Carbon Dioxide Emissions, but these indexes only partially reflect carbon dioxide emission performance. Data Envelopment Analysis (DEA) brings many factors related to carbon dioxide emission into the parameters frontier production function, and further gets an overall efficiency evaluator of carbon dioxide emission performance, i.e., Malmquist $CO_2$ Emission Performance Index (MCPI). It was first introduced by Zhou et al. (2010) and has been used to measure the dynamic change of carbon dioxide emission performance.

### 2.1 Environmental Dea Technique

Following Zhou et al. (2010) and Wang (2010), we further constitute a production rate index embracing $CO_2$ emission. Considering a production process in which the inputs are per capita material capital stock (denoted by $k$), per capita human capital stock (denoted by $h$) and per capita energy consumption (denoted by $e$), the desirable output is per capita GDP (denoted by $y$), and the undesirable output is per capita $CO_2$ emission. The set of production technology could be defined as follows:

$$T = \{(k, h, e, y, c) : \{(k, h, e), yielding(y,c)\} \quad (1)$$

$T$ is often assumed as a closed and finite set, indicating that limited inputs can only yield limited output. Inputs and desirable output are assumed to be strong disposable, i.e., if it satisfies that $(k, h, e, y, c) \in T$ and $(k', h', e')\geq(k, h, e)$(or $y'\leq y$), then $(k', h', e', y, c) \in T$ (or$(k, h, e, y', c) \in T$). In addition, it also needs to meet the conditions that the undesirable output is weak disposable and null-joint. That is to say,

(a) If $(k, h, e, y, c) \in T$ and $0\leq\theta\leq1$, then $(k, h, e, \theta y, \theta c) \in T$, which means that cost would appear if undesirable output is reduced and desirable output would reduce as the same proportion as undesirable output.

(b) If $(k, h, e, y, c) \in T$ and $c = 0$, then $y = 0$, which means that the desirable output must be zero if the undesirable output is zero.

Referring to the general method, we use nonlinear observation groups so as to put the production function into the framework of empirical analysis with non-parameter. The input and output vector of region $i$ can be written as $(k_i, h_i, e_i, y_i, c_i)$ where $i = 1,2,...I$. The equation of the piecewise linear production function is:

$T = (k_i, h_i, e_i, y_i, c_i)$:

$$\sum_{i=1}^{I} z_i k_i \leq \tau k, \sum_{i=1}^{I} z_i h_i \leq \tau h, \sum_{i=1}^{I} z_i e_i \leq \tau e, \sum_{i=1}^{I} z_i y_i \leq \tau y, \sum_{i=1}^{I} z_i c_i \leq \tau c,\ \tau \geq 1, z_i \geq 0, i=1,2,...,I. \quad (2)$$

Equation (2) is often called as environmental DEA technique within the framework in data enveloping analysis. Both Zhou et al. (2010) and Wang (2010) assume that the production technology is constant returns to scale (CRS), but actually assumption of variable returns to scale (VRS) is closer to the reality. Therefore, we follow the idea of Zhou et al. (2008) but assume that $T$ is VRS.

### 2.2 The Calculation of CMCPI

The measurement models include input-orientated and output-orientated model. The former aims to minimize the inputs at a given output and the latter aims to maximize the outputs at a given input. Follow Tyteca (1997), we choose output-orientated measurement model and define the efficiency exponential of the undesirable output is the reciprocal of Sheperd $CO_2$ output distance functions, namely,

$$\mathrm{D}_v\left(k,h,e,y,c\right)=\sup\left\{\mu:\left(k,h,e,y,y/\mu\right)\in T\right\} \quad (3)$$

Equation (3) calculates the most expected $CO_2$ emissions to measure the emission performance in each region during a specified period. Base on this, we can compute MCPI and further get CMCPI to observe the variance of $CO_2$ emission performance along the time. Given period $t$ and period $s(t<s)$, $\mathrm{D}_v^t\left(k_i^t,h_i^t,e_i^t,y_i^t,c_i^t\right)$ and $\mathrm{D}_v^s\left(k_i^t,h_i^t,e_i^t,y_i^t,c_i^t\right)$ are Sheperd $CO_2$ output distance functions with inputs during period $t$ and technology during period $t$ to period $s$. $\mathrm{D}_v^t\left(k_i^s,h_i^s,e_i^s,y_i^s,c_i^s\right)$ and $\mathrm{D}_v^s\left(k_i^s,h_i^s,e_i^s,y_i^s,c_i^s\right)$ are Sheperd $CO_2$ output distance functions with inputs during period $s$ and technology during period $t$ to period $s$. Then we define MCPI as:

$$MCPI_i\left(t,s\right)=\left[\frac{\mathrm{D}_v^t\left(k_i^t,h_i^t,e_i^t,y_i^t,c_i^t\right)\bullet \mathrm{D}_v^s\left(k_i^t,h_i^t,e_i^t,y_i^t,c_i^t\right)}{\mathrm{D}_v^t\left(k_i^s,h_i^s,e_i^s,y_i^s,c_i^s\right)\bullet \mathrm{D}_v^s\left(k_i^s,h_i^s,e_i^s,y_i^s,c_i^s\right)}\right]^{1/2} \quad (4)$$

$MCPII_i(t,s)$could measure the change of carbon dioxide emission performance from period $t$ to period $s$. $MCPII_i(t,s)>1$ (or $MCPII_i(t,s)<1$) implies that the carbon dioxide emission performance is better (or worse). Similar to Malmquist production exponential, MCPI can also be decomposed as Efficiency Change (EFFCH) and Technology Change (TECHCH), and

$$EFFCH_i\left(t,s\right)=\frac{\mathrm{D}_v^t\left(k_i^t,h_i^t,e_i^t,y_i^t,c_i^t\right)}{\mathrm{D}_v^s\left(k_i^s,h_i^s,e_i^s,y_i^s,c_i^s\right)} \quad (5)$$

$$TECHCH_i\left(t,s\right)=\left[\frac{\mathrm{D}_v^s\left(k_i^t,h_i^t,e_i^t,y_i^t,c_i^t\right)\bullet \mathrm{D}_v^s\left(k_i^s,h_i^s,e_i^s,y_i^s,c_i^s\right)}{\mathrm{D}_v^t\left(k_i^t,h_i^t,e_i^t,y_i^t,c_i^t\right)\bullet \mathrm{D}_v^t\left(k_i^s,h_i^s,e_i^s,y_i^s,c_i^s\right)}\right]^{1/2} \quad (6)$$

EFFCH will measure the catch-up effect, i.e., the relative changes of carbon dioxide emission performance during period $t$ to period $s$ constrained with the production frontier. TECHCH will measure the Shift Effect of the production frontier, i.e., the quantization of the production technology during period $t$ to period $s$ in region $i$. In our study, we suppose that $t = s$-1 and apply statistical software DEAP2.1 to estimate the carbon dioxide emission performance indexes of 30 provinces in China during 1998 to 2010, assuming that the production technology is VRS. Then, following Wang (2010), we set the carbon dioxide emission performance indexes of each province in 1998 as a group of benchmarks, and accumulate the subsequent years' MCPI to get the estimates of CMCPI, which reflect the cumulative changes of carbon dioxide emission performance among China's different provinces.

## 3. MODEL, VARIABLES AND DATA

### 3.1 Model and Variables

The method to deduce the employment demand equation follows Barrell and Pain (1997). Suppose that the production function is in the form of modified CES[7]:

$$Y = A(t)\left[ sK^{-\rho}+(1\text{-}s)L^{-\rho} \right]^{-v/\rho} \tag{7}$$

where $K$, $L$ denotes the producer's capital stock and labor employed, respectively; $A(t)$ denotes degree of the general technical progress along the time[8]; $v$ denotes the parameters of returns to scale; $s$ denotes the distribution parameters of input share in the production; and $\rho$ denotes the substitution parameters of production factors. The elasticity of substitution $\sigma$ could be measured by $1/(1+\rho)$, and the production function is in the form of Cobb-Douglas if $\rho = 0$.

The technology specified in Equation (7) is Hicks neutral, but some scholars think that Harrod-neutral technological progress[9] should be much closer to China's reality at this stage (Li & Wang, 2009). Therefore we adopt a modified CES production function with Harrod-neutral technological progress. That is,

$$Y = \left[ sK^{-\rho}+(1\text{-}s)(A_0e^{\lambda t}L)^{-\rho} \right]^{-v/\rho} \tag{8}$$

Differentiating on $L$ in equation (8), yielding

$$\frac{\partial Y}{\partial L}=A_0v(1\text{-}s)e^{\lambda t}Y^{(1+v/\rho)}(A_0e^{\lambda t}L)^{-(1+\rho)} \tag{9}$$

$W$ is supposed to be the real average wage. Since

$$\frac{\partial Y}{\partial L}=W \tag{10}$$

Then,

$$W=A_0v(1\text{-}s)e^{\lambda t}Y^{(1+v/\rho)}(A_0e^{\lambda t}L)^{-(1+\rho)} \tag{11}$$

Taking logarithm on both sides of equation (11), yielding

$$\ln L=-\frac{1}{1+\rho}\ln W+\frac{\rho+v}{\rho(1+\rho)}\ln Y+\frac{\ln v+\ln(1+s)\text{-}\rho\ln A_0-\rho\lambda t}{1+\rho} \tag{12}$$

where the coefficient of ln $W$ would be negative if $1/1+\rho>0$, and the coefficient sign of ln $Y$wouldn't be determined if $\rho>\text{-}1$ and $v$ was around 1. According to equation (12) and for our purpose in this study, we construct the econometric model of employment demand equation as equation (13) shows.

$$\ln L_{i,t}=\eta_i+\psi_t+\beta_0+\beta_1 CMCPI_{i,t}+\beta_r X_{i,t}+\gamma_1 CMCPI_{i,t}\bullet D_1+\gamma_r X_{i,t}\bullet D_1+u_{i,t} \tag{13}$$

$$\ln L\_int_{i,t}=\eta_i+\psi_t+\beta_0+\beta_1 CMCPI_{i,t}+\beta_r X_{i,t}+\gamma_1 CMCPI_{i,t}\bullet D_1+\gamma_r X_{i,t}\bullet D_1+u_{i,t} \tag{14}$$

$$\ln L\_low_{i,t}=\eta_i+\psi_t+\beta_0+\beta_1 CMCPI_{i,t}+\beta_r X_{i,t}+\gamma_1 CMCPI_{i,t}\bullet D_1+\gamma_r X_{i,t}\bullet D_1+u_{i,t} \tag{15}$$

In Equation (13), $\beta_0$ is constant term of the model, and $\eta_i$, $\psi_t$(r=2,3,4...) represents the unobservable region effect and time effect, respectively. The economic descriptions of other variables are summarized as follows.

ln $L_{i,t}$: The total employment of province $i$ in period $t$.

$CMCPI_{i,t}$: Cumulative Malmquist Carbon Dioxide Emission Performance Index if its estimated coefficient is positive, then it implies that a higher carbon dioxide emission performance could increase employment and vice versa.

$X_{i,t}$: A group of control variables to control other factors that would affect employment. In this paper, we choose the average real wage, market size and marketization degree as control variables.

ln $w_{i,t}$: Average real wage, measured by the average wage paid to employees in cities and towns. Theoretically

[7] Cobb-Douglas production function boasts a constant substitution elasticity of capital and labor, namely 1. There are many empirical grounds of argument that the substitution elasticity of capital and labor is always less than 1(Yang, 2009). CES production function isn't constrained with this empirical find and is more general to analyze production problems. Since the original CES production function introduces technology as a constant parameter independent to other factors, the technology doesn't change even at different periods. So we applied the augmented CES production function to take the technology movement into account, which is closer to the reality.

[8] Here, $A(t) = A_0e^{\lambda t}$, where $\lambda$ approximately measures the annual technological progress rate.

[9] The forms of neutral technical progress include Hicks neutral, Harold neutral and Solow neutral. The expression of Hicks neutral technical progress is $Y = A(t)F(K,L)$, reflecting the case in which the labor efficiency and capital efficient synchronously improve. Harold neutral technical progress is expressed as $Y = F(K,A(t)L)$, describing a technology progress caused by the improvement of labor efficiency. Solow neutral technical progress $Y = F(A(t)K,L)$, describing a technology progress caused by the improvement of capital efficiency.

its coefficient should usually be negative ceteris paribus.

$Msize_{i,t}$: Market size measured by the per capita GDP. Considering that there's more or less local market effect, we guess that the region with a larger market would attract more foreign direct investment and create more employment opportunities.

$Mindex_{i,t}$: The degree of marketization, measured by the index of marketization. Generally, a higher degree of marketization implies a more efficient allocation system of local factors to make better use of labor force. So its estimated coefficient is expected to be positive.

$D_1$: A dummy variable to discuss whether there are differences among different regions on the employment effect of $CMCPI_{i,t}$.Take $D_1$=1 if province $i$ is located in Eastern China, and take $D_1$=0 otherwise.

In order to examine the employment structure effect of $CO_2$ emission performance in China's different regions, we choose the logarithms of employments in energy-intensive industries[10] and low-power industries, denoted by $\ln L\_int_{i,t}$ and $\ln L\_low_{i,t}$, as the dependent variables (see Equations (14) and (15)). If the estimated coefficient of $CMCPI_{i,t}$ is significantly negative in Equation (14) and significantly positive Equation (15), the deduction could be drawn that low-carbon economy would help to improve the employment structure by driving employment from energy-intensive industries to low-power industries.

### 3.2 Data

The sample data are collected during 1998-2010 in China's 30 provinces because: (a) China started its action of energy saving and mitigation with the implementation of *the Energy Conservation Law of the People's Republic of China* in 1998; (b) it was a critical period when China switched to a market economy after the Asian financial crisis, during 1998 to 2010. Allowing for the fact that the policy of China's energy saving and mitigation was more intensively carried out during the 11th Five-Year Plan (2006-2010), we divide the sample time period into two intervals, 1998-2005 and 2006-2010.

In this paper, we classified China's 30 provinces into three zones, Eastern China, Central China and Western China[11]. The data sources and data processing are described as follows.

Per capita material capital stock (denoted by $k$): following Hall and Jones (1999), we use perpetual inventory method[12] to calculate material capital stock (denoted by $K$), divided by the employment, yielding per capita material capital stock.

Per capita human capital stock (denoted by $h$): following Hall and Jones (1999), we apply Mincer equation to compute the human capital stock (denoted by $H$), divided by the employment, yielding per capita human capital stock. Suppose that human capital will improve the labor efficiency, and their relationship can be written as $H_i = e^{\varphi(Ei)}L_i$, where $\varphi(Ei)$ are piecewise linear functions, $Ei$ denotes the education year at different levels and $L_i$ denotes employment. Referring to the average education year summarized by Chen (2009), we partition the education years of different levels into five categories: 1 year for illiteracy or semi literacy, 6 years for primary degree, 9 years for middle school degree, 12 years for high school degree and 16 years for college degree or above[13]. In view that there are not data published on return to education in China, we refer to the research of Hossain (1997), who estimate that the return to education for less than (or equal to) 6 years would be 0.144, 6 to 12 years be 0.129 and more than 12 years be 0.113[14]. Accordingly, we compute the weighted per capita material capital stock[15].

[10] Following Gong and Shen (2011), we classify all the industries into high energy consumption industries and low energy consumption industries, with energy consumptions per GDP as standard. Industries consuming more than (or equal to) 1 ton standard coal per 10 thousand GDP are classified as high energy consumption industries, the others are low energy consumption industries. High energy consumption industries include ferrous metal smelting and rolling processing industry, chemical raw materials and chemical products manufacturing, non-metal mineral products industry, non-ferrous metal smelting and rolling processing, oil processing coking and nuclear fuel industry, electric heating power production and supply industry, gas production and supply industry, the coal mining and washing industry, ferrous metals mining and dressing, water production and supply industry, and chemical fiber industry and oil and gas mining industry.

[11] According to China's National Bureau of Statistics, Eastern China includes 11 provinces, i.e., Liaoning, Hebei, Beijing, Tianjin, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong and Hainan; Central China includes 8 provinces, i.e., Heilongjiang, Jilin, Henan, Shanxi, Hubei, Hunan, Jiangxi and Anhui; Western China includes 11 provinces, i.e., Inner Mongolia, Xinjiang, Gansu, Qinghai, Shaanxi, Ningxia, Sichuan, Chongqing, Yunnan, Tibet, Guizhou and Guangxi. Due to the incompleteness of Data in Tibet, we knock Tibet out of our sample.

[12] The formula of perpetual inventory method is $K_t=I_t+(1-\delta)K_{t-1}$ whose economic meaning is that the observed capital stock $K_t$ is the sum of net capital stock $(1-\delta)K_{t-1}$ (where $\delta$ denotes the depreciation rate, taking 6% in this paper) in last accounting year and the new investment $I_t$ in the observed accounting year. In this paper, we set 1998 as the base year, referring to Hall and Jones (1999) to imitate the physical capital stock of 1998, which is $K^{i}_{98}/I^{i}_{98}/(g^{i}+\delta)$, where $g^{i}$ is the average annual geometric growth rate of the physical capital stock during 1998 to 2010.

[13] People with illiteracy or semi literacy can accumulate human resource capital by learning in doing and experience, so we take the education year as 1 but not 0.we unite the education years of junior college, undergraduate and postgraduate into 16 years.

[14] Hossain (1997) computes the private and social rate of returns at different levels of education degrees. The private provided by him is 0.18, 0.134, and 0.151, but the values are greatly related to the specific history and not available nowadays. Therefore, we borrow the social rate of returns from Hossain (1997), and refer to Tamura (1991) who finds that the return of human capital is in an inverse-U shape.

[15] Different from the form studies, we weight the human capital at different levels of education, and the formula is $H_i = e^{0.144}\bullet(1L_{i,E1}+6L_{i,E6})+e^{0.129}\bullet(9L_{i,E9}+12L_{i,E12})+16e^{0.113}L_{i,E16}$, where $H$ is the human capital stock in province $i$, and $L_{i,E1}$, $6L_{i,E6}$, $L_{i,E9}$, $L_{i,E12}$, $L_{i,E16}$ denotes the employment at different levels of education.

Degree of marketization: we collect the marketization indexes of China's 30 provinces as a proxy for the degree of marketization. The proxy data during 1998 to 2009 are taken from report *Marketization Index in China 2011: The Relative Marketization Process in Each Region* edited by Fan and Wang. We estimate the marketization index in 2010 by exponential moving average method.

**Table 1**
**$CO_2$ Emission Coefficients of the Main $CO_2$ Emission Sources**

| Source | Coal | Coke | Diesel | Petrol | Kerosene | Fuel Oil | Gas | Cement |
|---|---|---|---|---|---|---|---|---|
| Coefficient | 1.647 | 2.848 | 3.150 | 3.045 | 3.174 | 3.064 | 2.090 | 0.376 |

*Note.* The unit of gas $CO_2$ emission coefficient is t $CO_2$/km$^3$, and the unit of the others is t $CO_2$/t.

The main sources of $CO_2$ emissions include fossil fuel burning and cement production. It's necessary to classify and summarize energy consumptions since the $CO_2$ emissions from burning the same amount of different kinds of energy remain distinctive. Considering the availability and completeness of data concerned, we add up the consumptions of coal, coke, diesel, petrol, kerosene, fuel oil and gas to reckon up the total energy consumptions in China's 30 provinces[16]. According to the United Nations Inter-governmental Panel on Climate Change and the study of Du (2010), we estimate $CO_2$ emission coefficients of the main $CO_2$ emission sources (see Table 1), and calculate the total $CO_2$ emissions in different provinces.

The data on the energy consumptions of different kinds are from *China's Energy Statistics Yearbook* during 1998-2010 and the data of cement production are from CEI net Database. The data on GDP, the social fixed asset investment, population, average wages in urban and towns and retail price index are from *Statistical Yearbook of China* during 1998-2010. The education levels of employment are from *Labor Statistical Yearbook of China* during 1998-2010. All the data concerning foreign affairs are exchanged into CNY at the corresponding average annual RMB-Dollar reference rate, and all nominal data of the retail price indexes are deflators based in 1998.

## 4. THE EMPIRICAL ANALYSIS

### 4.1 The Statistical Description of the Sample Data

#### 4..1.1 The Regional Differences on Carbon Dioxide Emissions in China

From Figures 1 and 2 we can see that both the carbon dioxide emissions and carbon dioxide production rate have increasing trends, and they are highest in Eastern China, followed by Central China and then Western China. Carbon dioxide emissions and carbon dioxide production rate of Eastern China are far higher than that of Central and Western China whose emissions and rates are not far away from each other. In addition, the carbon dioxide production rates have been raised significantly every year except in 2005, when there appear outstanding emission peaks in all regions during 2003-2006, but obviously go down after them.

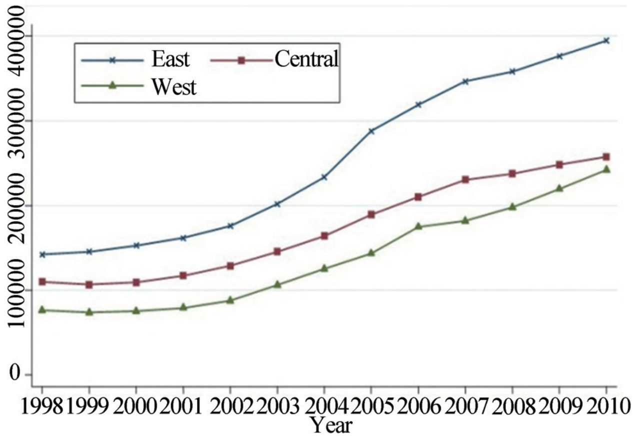


**Figure 1**
**$CO_2$ Emissions among Different Different Regions of China 1998-2010 (Unit: 10,000 tons)**

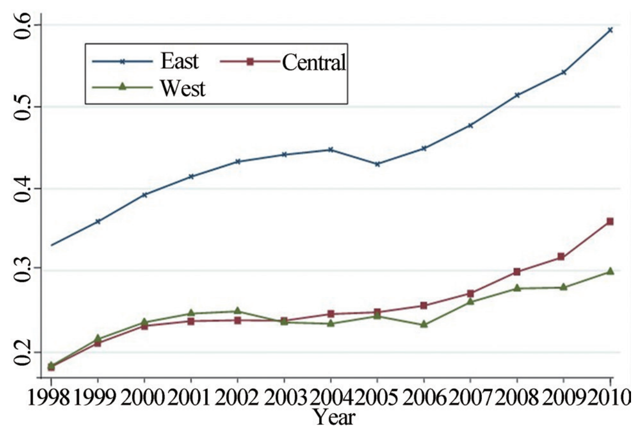


**Figure 2**
**$CO_2$ Productivity Rate among Different Regions of China 1998-2010 (Unit: 10,000 Yuan/ t $CO_2$)**

#### 4.1.2 Regional Differences on Employment of Energy-Intensive Industries in China

As Figure 3 and 4 show, Eastern China has been leading in both the employment scale and proportion of energy-intensive industries, followed by Central China and then Western China. Roughly divided by 2002, there are two intervals during 1998-2010: (a) during 1998 to 2002, the employment scale and proportion of energy-intensive industries had been going down year by year, and this trend was highly synergetic among the three regions which was probably related to state-owned enterprises

[16] According to *China's Oil Strategic* published by China's National Planning Commission of Macroeconomic Research Institute in 2002, China had manufactured more than 80 percent of crude oil into oil products such as oil diesel, gasoline, kerosene, fuel oil, and the leftover is inputted in chemical industry. So we just examine the terminal consumptions of oil diesel, gasoline, kerosene, fuel oil when computing the oil consumptions.

(SOEs) reform; (b) during 2002-2010, there has been a trend that both the employment scale and proportion of energy-intensive industries increase in China, but the trend is not so noticeable in Eastern China where there has even been a reverse trend since 2008. Central China and Western China have kept increasing trend at this interval. For any individual province, Beijing and Shanghai have been a decreasing trend on both the employment scale and proportion of energy-intensive industries during 1998-2010, while the others share similar characteristics to the above two intervals.

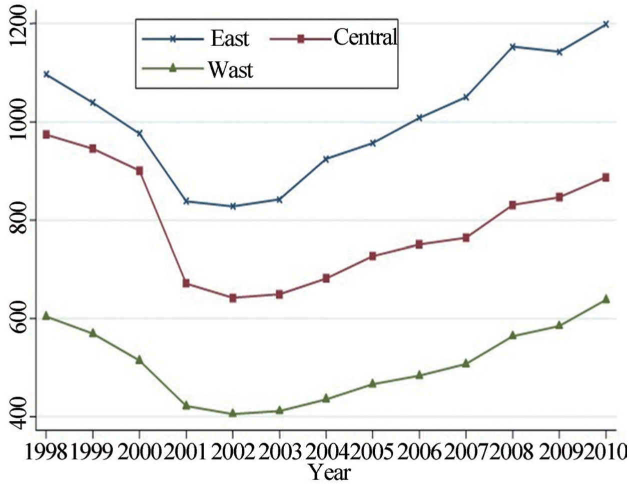


**Figure 3**
**Employment of Energy-Intensive Among Different Regions in China 1998-2010 (Unit: 10,000 persons)**

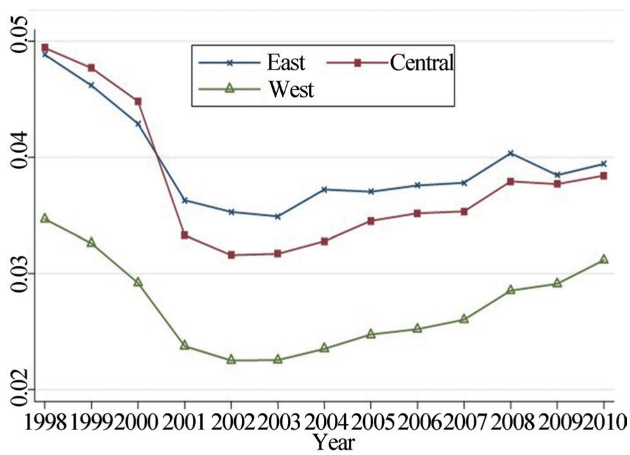


**Figure 4**
**Employment Proportions of Industries Energy-Intensive Industries Among Different Regions in China 1998-2010 (Unit: %)**

#### 4.1.3 The Regional Differences on Carbon Dioxide Emissions Performance Indexes in China

The annual geometric average turns out a stance that MCPI is "highest in Eastern China, followed by Western China and lowest in Central China" (see Table 2). The same story happens to the CMCPI[17] (see Figure 5). Among those provinces whose estimated MCPI are larger than 1, Beijing, Shanghai, Tianjin, Zhejiang, Hainan, Guangdong, Jiangsu and Fujian are located in Eastern China; Xinjiang, Ningxia and Shaanxi in Western China and only one province, Hubei, in Central China. Hunan, Jiangxi and Shanxi in Central China as well as Inner Mongolia and Guizhou in Western China have been ranking at the end. The average MCPI during 1998-2010 is 1.023 in Eastern China, 0.974 in Central China and 0.993 in Western China. Additionally, among the three regions, only Eastern China has an increasing CMCPI, and both Central and Western China's CMCPI is decreasing.

**Table 2**
**Average MCPI among Provinces in China 1998-2010**

| | | | | | |
|---|---|---|---|---|---|
| Beijing | 1.077 | Fujian | 1.007 | Gansu | 0.979 |
| Shanghai | 1.060 | Hubei | 1.003 | Guangxi | 0.976 |
| Tianjin | 1.049 | Qinghai | 1 | Jilin | 0.976 |
| Xinjiang | 1.029 | Yunnan | 1 | Sichuan | 0.975 |
| Zhejiang | 1.026 | Hebei | 0.993 | Henan | 0.970 |
| Hainan | 1.025 | Anhui | 0.989 | Hunan | 0.966 |
| Ningxia | 1.024 | Liaoning | 0.987 | Inner Mongolia | 0.964 |
| Guangdong | 1.023 | Chongqing | 0.983 | Jiangxi | 0.959 |
| Jiangsu | 1.017 | Shandong | 0.982 | Guizhou | 0.947 |
| Shaanxi | 1.017 | Heilongjiang | 0.980 | Shanxi | 0.944 |

We think it's somewhat reasonable for this situation. The Eastern China has best performed on economic development and technological progress comparing with Central and Western China. With the gradual transformation of economic pattern, the continuous transfer of energy-intensive industries and the remarkable development of low-carbon industries, Eastern China is liable to fewer carbon emissions and leads in MCPI in China. The ecological environment in Western China has been deteriorating since the Go-west Campaign and greatly increasing its carbon emissions. Even so, the MCPI in Western China is possible to be higher than Central China resulted from the reality that Western China is least developed in China, and its degree of industrialization is less developed to generate so many carbon emissions. For Central China, on one hand, it has developed an industry structure characterized by energy-intensives and paid not sufficient attentions towards energy saving and mitigation guided by Rise of Central China Plan; on the other hand, Central China is the frontier to undertake the energy-

[17] This order is similar to Yang and Hu (2010), but is different from Wang et al (2010) who think the order should be Eastern China, Northeastern China, Central China and Western China. We put up with two possible reasons: (1) the data used in this paper are different from theirs. We use per capita indicators but not gross indicators, and human resource capital input but not employment input; (2) the assumptions are different on that this paper assume the production technology is variable returns to scales

intensive industries transferred from Eastern China. The internal and external elements determine Central China to be an undertaker of carbon emissions in China and to have boasted a MCPI even lower than Western China since 2002.

Sorted by the order in Table 2, the variances of the averages on the MCPI and the decompositions during 1998 to 2010 in each province are graphed (see Figure 6) as Figure 6 shows, among the two decompositions of MCPI, the efficiency change (EFFCH) varies insignificantly, floating around 1 within a band of plus or minus 1%; the technology change (TECHCH) gets well along with MCPI and their correlation coefficient is as high as 0.9731, while the EFFCH is merely 20.86% correlated to MCPI. The correlation between EFFICH and MCPI and that of TECHCH and MCPI test and verify what Shen (2007) discovers in his study. He finds that the change in total factor productivity (TFP) of China mainly comes from TECHCH rather than EFFICH and the conclusion will hold under the circumstance of carbon dioxide emissions or energy consumptions.

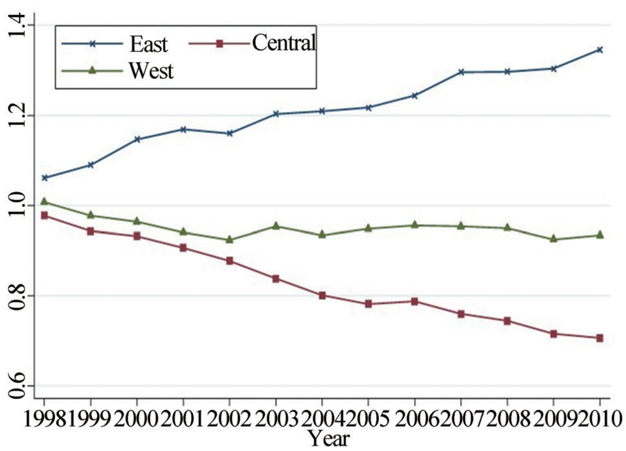


**Figure 5**
**The Regional Dynamic Changes on MCPI in China**

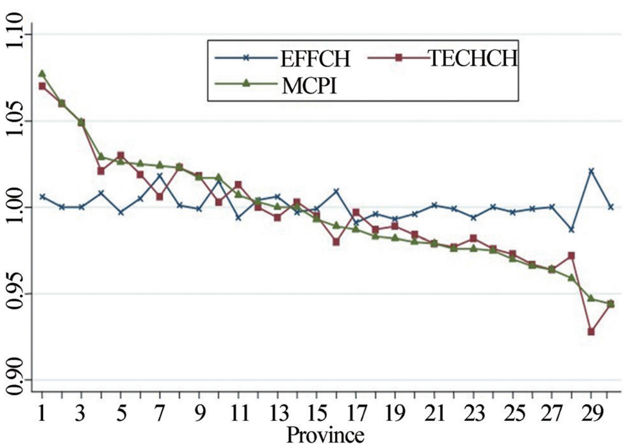


**Figure 6**
**The Averages and Decompositions of MCPI among Provinces in China**

## 4..2 Panel Data Analysis

### 4.2.1 Estimation Method

Usually, it's costly for employers to cut off staffs, while the plan to recruit new employees is decided by the employment situation and economic prospects. In other words, employment in the former stage could have an impact on this stage, so we extend Equation (13)[18] as a dynamic panel data model as Equation (16).

$$\ln L_{i,t} = \eta i + \psi t + \beta_0 + \omega \ln L_{i,t-1} + \beta_1 CMCPI_{i,t} + \beta_r X_{i,t} + \gamma_1 CMCPI_{i,t} \bullet D_1 + \gamma_r X_{i,t} \bullet D_1 + u_{i,t} \quad (16)$$

In Equation (16), variable $Msize_{i,t}$ may interact with variable $\ln L_{i,t}$ and the parameters estimated by using OLS, fixed effect model or random effect model would be biased. Arellano and Bond (1991) propose the generalized moment method (GMM) to avoid the possible error. Supposing that the predetermined variables are independent of the spot residuals, they take the first difference on the model and all the lagged terms of the dependent variable are introduced the model as instrumental variables (IV) (this method is called Difference GMM). However, if there are too many lagged terms in different GMM model, the problem of weak IV will easily happen. To solve this problem, Arellano and Bond and the coming scholars have done lots of work.

Arellano and Bover (1995) return to the level equation before taking difference and development level GMM method by specifying all the differences on the lagged terms of the dependent variable as IV for the first-order lagged terns of the dependent variable. Furthermore, Blundell and Bond (1998) integrate the advantages of difference GMM and level GMM and estimate parameters in difference and level equations as a whole system (this method is called system GMM method). The main ideas of system GMM are: (a) to eliminate the fixed effect by difference equation and to specify the level terms of dependent variables as IV for its different terms; (b) to solve the problem of weak IV with augmented IV.

System GMM estimation includes one-step estimation and two-step estimation. Windmeijer (2005) finds that two-step estimation will underestimate the standard deviation of a small sample size, but a corrected two-step estimation will be more robust and efficient. This paper applies GMM two-step estimation with Windmeijer correction.

Sargan Test and Hansen Test are often used to judge the identification of instrumental variables and to test their efficiency, and their null hypothesis is that the instrumental variables are jointly efficient. Sargan Test is carried on the conditional homoskedasticity assumption while Hansen Test is more general, so we have a Hansen Test in this paper. To satisfy the requirements that the augmented IV is efficient and strongly exogenous in the system GMM model comparing to different GMM

[18] Equations (14) and (15) are also extended into equations (17) and (18).

model, we need to have a Difference Hansen Test on both models. The estimators in the two models are Difference Hansen (GMM) Test and Difference Hansen (iv) Test, respectively, and the former test has a null hypothesis that the additional instrumental variables are efficient, while the latter test has a null hypothesis that the specified predetermined variables are strongly exogenous.

The consistency condition of GMM estimation requires that residuals of the difference terms don't have second-order serial correlation, so we carry on AR(2) test to judge whether the original residual series is auto-correlated. In the end, we take Wald Test to judge the joint significance of the model. Taking the policy effect into consideration, we divide the sample data into two groups, 2005 as watershed. Longitudinally, the first group covering 1998-2005 spans 8 years and the second group covering 2006-2010 spans 5 years; latitudinally, there are 30 observed objects. The sample data qualify the property of "large N, small T" required in dynamic panel data analysis.

We will estimate the average employment effect of CMCPI by the following steps. First of all, we explore what effects may carbon dioxide performance have on the employment structure in different level energy-intensive industries and the total employment, and the dependent variables are CMCPI and the first-order lagged terms of the explained variable (see Table 3). Secondly, we include regional dummies to inspect the possible regional differences on CMCPI's employment effect (see Table 4). To test the robustness of the estimations in Table 3 and 4, we continue to include control variables to inspect the estimated coefficient of CMCPI and its significance (see Table 5).

#### 4.2.2 Estimation Results and Discussion

As we can see from Tables 3, 4 and 5, *P* value of AR(2) Test are all above 0.05, so none of the three models estimated exists second-order residual autocorrelations. *P* values of Hansen Test are all above 0.05, which manifests that the instrumental variables are not over-identified, i.e., the IV is not exogenous in the system GMM estimation. Both difference Hansen Tests do not reject the null hypotheses at 5% significance level. *P* values of Wald Test are all 0, manifesting that the independent variables are jointly significant. The estimated coefficient signs of the first-order lag of the dependent variables are significantly positive, and are all fall within domain bounded by the coefficient estimated in fixed effect model and OLS regression[19], which illustrates that the estimation results don't seem to be too biased (Bond, 2002). Additionally, the value of the estimated coefficients discovers that the employment in China has a lot of "inertia", that is to say, the employment in the spot period is significantly related to the former period. The results manifest that the models are properly specified. We are going to analyze the employment effect of CMCPI in China in detail.

(a) Industrial differences

From the second and third column in Table 3, we can find that CMCPI has significant negative effects on employment in China's energy-intensive industries during the two intervals, 1998-2005 and 2006-2010, and the average effects are 0.058 and 0.029, respectively. As the last four columns in Table 3 shows, CMCPI has a significantly positive effect on the employment in China's low-power industries and the total employment. Based on the analysis above, we can find that a higher CMCPI would result in a worse employment situation in energy-intensive industries, but a better employment in low-power industries and so as the total employment.

**Table 3**
**The Estimation Results of Employment Effect of CMCPI in Energy-intensive industries in China**

| Dependent variables(DV) | ln*L*_int | | ln*L*_low | | ln*L* | |
|---|---|---|---|---|---|---|
| Independent variables | 98-05 | 06-10 | 98-05 | 06-10 | 98-05 | 06-10 |
| Constant terms | $0.311^{***}$ | 0.044 | $0.069^{*}$ | $-0.070^{*}$ | 0.052 | $-0.092^{***}$ |
| | (0.117) | (0.104) | (0.039) | (0.038) | (0.038) | (0.036) |
| AR(1) for DV | $0.928^{***}$ | $0.987^{***}$ | $0.989^{***}$ | $0.988^{***}$ | $0.981^{***}$ | $0.988^{***}$ |
| | (0.026) | 0.023 | (0.005) | (0.005) | (0.004) | (0.004) |
| CMCPI | $-0.058^{*}$ | $-0.029^{*}$ | $0.023^{*}$ | $0.026^{***}$ | $0.022^{*}$ | $0.025^{***}$ |
| | (0.030) | (0.016) | (0.013) | (0.006) | (0.013) | (0.006) |
| Observations | 210 | 150 | 210 | 150 | 210 | 150 |
| Wald Test | 0 | 0 | 0 | 0 | 0 | 0 |
| AR(1) Test | 0.001 | 0.002 | 0.035 | 0.084 | 0.054 | 0.081 |
| AR(2) Test | 0.194 | 0.363 | 0.530 | 0.782 | 0.614 | 0.926 |
| Hansen Test | 0.279 | 0.995 | 0.360 | 0.993 | 0.279 | 0.987 |
| Difference Hansen (GMM)Test | 0.088 | 0.976 | 0.227 | 0.985 | 0.138 | 0.968 |
| Difference Hansen(iv) Test | 0.249 | 0.993 | 0.281 | 0.992 | 0.236 | 0.991 |

*Note.* ① the estimation results are finished with STATA12.0 and the syntax used is xtabond2; ② the number in brackets below the estimated coefficients are standard deviations and P values below the related econometric tests; ③asterisk ***, **and * represent the significance at the levels of 1%, 5% and 10%.

(2) Regional differences

The regional employment differences of CMCPI could be distinguished by including dummy variable $D_1$ and its interactions with CMCPI, which represents the observation is in Eastern China when $D_1$ is taken 1, and in Central or Western China when took 0. Then, the estimated coefficient of CMCPI reflect the impacts of CMCPI have on the employment in Central and Western China, and that of the interaction terms reflects the regional differences on employment effects of CMCPI.

[19] Bond (2002) argues that the first-order lagged term of dependent variable would be underestimated by fixed effect estimation, and overestimated by OLS estimation. To save the thesis length, we don't report the estimations results using these two estimation methods.

The sum of the two coefficients can measure the total employment effect of CMCPI in Eastern China.

As Table 4 shows, CMCPI significantly impedes employment of energy-intensive industries in Central and Western China only in the period 1998-2005, but it's significant in both periods 1998-2005 and 2006-2010 in Eastern China. The third column in Table 4 indicates that the average negative employment effect of CMCPI is 0.087 in Eastern China's energy-intensive industries during 2006 to 2010, 0.048 higher than Central and Western China. From the aspect of low-power industries, the average positive employment effect of CMCPI in Eastern China is significantly larger than Central and Western China.

**Table 4**
**The Estimation Results of Employment Effect of CMCPI in Low-Power Industries in China**

| Dependent variables(DV) | ln*L*_int | | ln*L*_low | | ln*L* | |
|---|---|---|---|---|---|---|
| Independent variables | 98-05 | 06-10 | 98-05 | 06-10 | 98-05 | 06-10 |
| Constant terms | 0.381** | -0.066 | 0.085*** | -0.008 | 0.096** | -0.035 |
| | (0.172) | (0.167) | (0.035) | (0.039) | (0.047) | (0.082) |
| AR(1) for DV | 0.930*** | 0.979*** | 0.989*** | 0.993*** | 0.989*** | 0.992*** |
| | (0.031) | (0.034) | (0.004) | (0.005) | (0.006) | (0.009) |
| CMCPI | -0.159** | -0.039 | 0.006 | 0.008 | 0.004 | 0.007 |
| | (0.068) | (0.056) | (0.012) | (0.010) | (0.011) | (0.007) |
| CMCPI·$D_1$ | 0.058** | -0.048* | 0.009** | 0.011** | 0.008** | 0.009* |
| | (0.029) | (0.027) | (0.004) | (0.005) | (0.004) | (0.005) |
| Observations | 210 | 150 | 210 | 150 | 210 | 150 |
| Wald Test | 0 | 0 | 0 | 0 | 0 | 0 |
| AR(1) Test | 0.000 | 0.010 | 0.027 | 0.083 | 0.036 | 0.089 |
| AR(2) Test | 0.175 | 0.627 | 0.561 | 0.804 | 0.973 | 0.957 |
| Hansen Test | 0.406 | 0.996 | 0.604 | 0.997 | 0.503 | 0.991 |
| Difference Hansen (GMM) Test | 0.346 | 0.955 | 0.646 | 0.984 | 0.473 | 0.966 |
| Difference Hansen(iv) Test | 0.492 | 0.965 | 0.724 | 0.987 | 0.366 | 0.973 |

*Note.* ① the estimation results are finished with STATA12.0 and the syntax used is xtabond2; ② the number in brackets below the estimated coefficients are standard deviations and P values below the related econometric tests; ③asterisk ***, **and * represent the significance at the levels of 1%, 5% and 10%.

(3) Inter-temporal differences

Tables 3 and 4 indicate that the employment effects of CMCPI vary dynamically during the two periods, 1998-2005 and 2006-2010. In this regard, the negative employment effect of CMCPI in energy-intensive industries are decreasing, from 0.58 to 0.29 in the whole China（see Table 3）, from 0.159 to 0.039 in Central and Western China (see Table 4), and from 0.101 to 0.087 (see Table 4) in Eastern China. In contrast, the total employment and structural effects of CMCPI in low-power industries are increasing, respectively from 0.023 and 0.022 to 0.026 and 0.025 in the whole China in table 3, from 0.015 and 0.012 to 0.019 and 0.016 in Eastern China in table 4, which is not significant in Central and Western China.

(4) Robustness test

As Table 5 shows, the CMCPI still has a significantly negative effect on employment in Eastern China's high energy-intensive industries in case that the control variables are included, and it still significantly promotes the total employment and employment in low-power industries in Eastern China. Dynamically, the negative effect is decreasing and the positive effect is increasing along the time, and the same happens without including control variables. So we can draw a conclusion that the analysis results on the employment effect of CMCPI in China are robust.

The estimated coefficient signs of the control variables are consistent with related economic theory. Noticeably, the real average wage doesn't significantly affect the employment in Central and Western China, but it has a significantly negative effect on Eastern China's employment. Without regard to the significance, we can see that the negative employment of the real average wage in Eastern China is smaller than that in Central and Western China. Generally speaking, the expansion of market size promotes employment in China, but the effect is greater and more statistically significant in Central and Western China than Eastern China, which may result from the regional strategies of rejuvenation in the sample period. The greater degree of marketization do favor to the employment promotion, but again, the effect is greater and more statistically significant in Central and Western China than Eastern China, which is probably because the lower degree of marketization in Central and Western China would create more employment opportunities.

**Table 5**
**The Estimation Results of Employment Effect of CMCPI in China**

| Dependent variables(DV) | ln*L*_int | | ln*L*_low | | ln*L* | |
|---|---|---|---|---|---|---|
| Independent variables | 98-05 | 06-10 | 98-05 | 06-10 | 98-05 | 06-10 |
| Constant terms | -1.091* | 0.308 | 0.037 | -0.151 | 0.015 | -0.251 |
| | (0.584) | (0.346) | (0.189) | (0.196) | (0.169) | (0.219) |
| AR(1) for DV | 0.968*** | 0.943*** | 0.988*** | 0.992*** | 0.983*** | 0.997*** |
| | (0.027) | (0.051) | (0.008) | (0.016) | (0.008) | (0.018) |
| CMCPI | -0.182*** | -0.032 | 0.006 | 0.009 | 0.007 | 0.007 |
| | (0.069) | (0.045) | (0.021) | (0.013) | (0.018) | (0.013) |
| CMCPI • $D_1$ | 0.043** | -0.102*** | 0.013* | 0.025** | 0.006 | 0.029*** |
| | (0.021) | (0.038) | (0.007) | (0.011) | (0.028) | (0.011) |
| lnw | 0.142 | -0.338 | -0.038 | -0.042** | 0.035 | -0.032 |
| | (0.103) | (0.242) | (0.041) | (0.021) | (0.038) | (0.028) |
| msize | 0.104*** | 0.327** | -0.034 | 0.031*** | 0.034** | 0.049*** |
| | (0.026) | (0.146) | (0.056) | (0.012) | (0.018) | (0.013) |
| mindex | 0.029*** | 0.012*** | 0.005 | -0.004 | 0.009** | -0.007 |
| | (0.011) | (0.005) | (0.006) | (0.006) | (0.004) | (0.008) |
| lnw • $D_1$ | 0.206** | 0.258** | -0.017 | 0.027** | -0.012*** | 0.029*** |
| | (0.096) | (0.123) | (0.053) | (0.013) | (0.005) | (0.011) |
| msize • $D_1$ | -0.169 | -0.269 | 0.005 | -0.025* | 0.024** | -0.044*** |
| | (0.131) | (0.327) | (0.054) | (0.014) | (0.011) | (0.017) |
| mindex • $D_1$ | -0.018* | 0.024*** | 0.002 | -0.001 | 0.002 | 0.001 |
| | (0.011) | (0.007) | (0.004) | (0.002) | (0.003) | (0.002) |
| Observations | 210 | 150 | 210 | 150 | 210 | 150 |
| Wald Test | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| AR(1) Test | 0.000 | 0.003 | 0.033 | 0.084 | 0.050 | 0.077 |
| AR(2) Test | 0.248 | 0.445 | 0.575 | 0.761 | 0.713 | 0.996 |
| Hansen Test | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Difference Hansen(GMM)Test | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Difference Hansen(iv) Test | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |

*Note.* ① the estimation results are finished with STATA12.0 and the syntax used is xtabond2; ② the number in brackets below the estimated coefficients are standard deviations and P values below the related econometric tests; ③asterisk ***, **and * represent the significance at the levels of 1%, 5% and 10%.

## CONCLUSION

In this paper, we measure the carbon dioxide emission performance indexes among provinces in China during 1998 to 2010 and then estimate the relationship between carbon dioxide emission performance indexes and the employment among different regions and industries using the system GMM method. The main conclusions are drawn as follows.

Firstly, the statistical description analysis suggests that the feature "highest in Eastern China, followed by the Central China and lowest in Western China" is possessed by the $CO_2$ emissions, $CO_2$ productivity, employment scale and proportion of energy-intensive industries, but the $CO_2$ emissions performance is characterized by "highest in Eastern China, followed by Western China and lowest in Central China". In addition, only Eastern China has an increasing trend on the cumulative $CO_2$ emissions performance, while Central and Western China have decreased one. Analyzing the decompositions of MCPI, we can find that the regional differences of MCPI are caused by technological changes but not efficient changes.

Secondly, the estimation results of system GMM method indicate that the $CO_2$ emissions performance has a descending handicap on the employment of energy-intensive industries and an ascending promotion on the employment of low-power industries in Eastern China. The promotion effect is larger and more statistically significant than Central and Western China. The conclusions are tested to be robust.

Thirdly, low-carbon economy affects employment more significantly in Eastern China than in Central and Western China. In Eastern China, a better the $CO_2$ emission performance would provide less opportunity for employment in high energy-intensive industries, but create more opportunity for employment in low-power industries, so the total employment will increase with a better $CO_2$ emission performance. But the same story doesn't happen in Central and Western China since the estimation results are not significant. Why it could happen may be caused by the differences on economic development stage, but the underlying reasons need further study. The dynamic changes demonstrate the strong employment aftereffect of $CO_2$ emission performance in low-power industries, and it needs to further discuss whether the mechanism is consistent.

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