Regional Carbon Emission Performance of Pig Production in China according to Malmquist-DEA Approach

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Abstract As pig production is a main contributor of greenhouse gas (GHG) emissions from livestock sector, the carbon emissions of pig production are attracting increasing attention, especially in the developing countries. Based on the panel data of 30 provinces in China from 2001 to 2012, this paper measures the provincial carbon emission performance (CEP) of pig production and we use a Malmquist DEA approach to analyze the decomposition which includes desirable and undesirable output. Furthermore, the regional disparity in carbon emission performance of pig production is also analyzed and finally the convergence is tested. The main results are as follows: (i) there are provincial differences in carbon emission performance changing of pig production in China, and the carbon emission performance of pig production in 30 provinces has a downward trend during this period; (ii) among China's three major economic regions, in terms of carbon emission performance of pig production, they are ranked in descending order as follows: Western China, Central China and Eastern China; (iii) convergence testing shows that there is a convergence trend for carbon emission performance both nationally and for the three regions.

Key words Carbon emission performance, Pig production, Malmquist DEA approach, Convergence

1 Introduction

The environmental impacts of livestock production are attracting increasing attention, especially the emission of GHGs[1]. Globally, the life cycle and supply chain of the domesticated animals as food account for 51% of all human-caused GHGs[2]. Currently, pork is the most widely consumed meat product in the world, and pig production is the second contributor of GHG emissions from livestock sector, with about 13% of total emissions related to livestock[3]. As predicted, by 2050 global pork consumption may increase by almost 40%[3]. Therefore, the greenhouse gas emission produced by pig will continue to rise. So, it is a significant task for the scholars to study how to effectively control the carbon emission. At present, the study on the carbon emission produced by pig includes the following aspects: given this, more and more researchers are conducting study on carbon emissions of pig industry, mainly from the following aspects: (i) research on calculation of pig producing carbon emissions. For instance, Hu et al. (2010)[4] and Chen et al. (2014)[5] measured the GHG emissions of China's pig production with respect to *Preliminary Guidelines for Greenhouse Gas Statistics*, introduced by the IPCC. Chao et al. (2014)[5] developed the carbon dioxide (CO_2) production model to quantify the CO_2 produced by pig respiration and CO_2 released from manure in the building; (ii) research on influencing factors of carbon emissions produced by pig. For example, Chao et al. (2014)[6] assessed the influences of animal mass, animal activity, and ventilation rate on CO_2 concentrations and emissions

in a fattening pig house with a partial pit ventilation system. Philippe et al. (2014)[1] argued that floor type, manure management, nutrition of the pigs as well as the climatic conditions inside the building principally influenced the GHG emissions from pig houses. Chen et al. (2014)[5] used the LMDI model to decompose the factors affecting GHG emissions of China's livestock, finding that economic factor had the most significant impact on GHG emissions; (iii) research on carbon reduction policy of pig production. Wang (2011)[7] suggested that we should develop low-carbon pig-raising by optimizing the breeding scale, disease controlling, waste processing, pig industrialization, piglet resources, feed supplying, barn building, resource recycling and dead pig treatment. Wu (2010)[8] also put forward similar recommendations for low-carbon pig production, such as promoting efficient hybrids to increase production levels, and applying fermentation-bed technology to solve environmental pollution problems. All of these researches have provided significant references for subsequent studies on carbon emissions of pig production. Nevertheless, much of the present literature in this field has limitations: firstly, the current researches on carbon emissions of pig production were mostly from one single perspective, with a comprehensive consideration that the literature about the efficiency and the disintegration of carbon emission produced by pig is not enough; secondly, with the deepening of studies on carbon emissions, the convergence theory in regional economic growth researches was introduced into environment economic researches, such as Strazicich and List (2003)[9], Aldy (2007)[10], Zhou and Nie (2012)[11], Dong et al. (2013)[12]. However, most of the existing researches are based on the whole national level and industry field, most of the researches are about the industry sector, and observed convergence testing for carbon emission performance of pig production is rare;

most importantly, the literature involving China's provincial carbon emission of pig production is extremely rare, as the largest pork producer and consumer, China produces about half of the world's pork, resulting in increasingly serious pollution problems. Consequently, this paper aims to calculate China's pig producing carbon emissions and its performance, and decompose the corresponding influencing factors utilizing the combined DEA and Malmquist Index method. Moreover, this study moves a step further to conduct a convergence test. The remainder of the paper is organized as follows: Section 2 describes the CEP model construction based on the Malmquist DEA and relevant variables; Section 3 presents and discusses the empirical results; Section 4 is about the conclusion of this research.

2 Model structure and variable data

2.1 DEA model construction The DEA method was put forward by Charnes *et al.* (1978)[13] to assess the efficiency of decision making unit (DMU) with multi-inputs and multi-outputs. The major advantage of DEA is that it does not impose any functional form on the frontier nor does it assume a particular distributional form for the inefficiency errors terms; this major advantage is a weakness for parametric frontier models[14]. Hence, it is widely utilized in many research fields[15]. This study used nonparametric DEA to construct China's pig production frontier and relevant indexes. The basic idea is to get environmental production frontier of China's pig industry through the envelope of all sample provinces, and further calculate environmental technology efficiency and Malmquist index using the directional distance function (DDF). According to Fare *et al.* (2007)[16], the environmental technology is defined as technical structure relation between outputs (including undesirable outputs) and elements of resource inputs. Environmental technology is different from traditional input-output technology structure, when investment is at a constant level, in order to reduce environmental pollution, it needs resource investment, and this will accordingly reduce investment of resources used to produce desirable outputs, leading to reduction of desirable outputs. Here we can model environmental technology with output set: for each DMU (province), inputs are denoted by $x = (x_1, \cdots, x_N) \in R_+^N$, desirable outputs by $y = (y_1, \cdots, y_M) \in R_+^M$, and undesirable output by $b = (b_1, \cdots, b_1) \in R_+^1$; let $(x^{k,t}, y^{k,t})$ be the production point of DMU k $(k = 1, \cdots K)$ in period t $(t = 1, \cdots T)$, then the production possibility set of environmental technology can be expressed as:

$$P^t(x^t) = \begin{cases} \sum_{j=1}^{J} z_j y_{j,m}^t \geq y_{j,m}^t, & m = 1, \cdots M; \\ \sum_{j=1}^{J} z_j b_{j,i}^t \geq b_{j,i}^t, & i = 1, \cdots I; \\ \sum_{j=1}^{J} z_j x_{j,n}^t \leq x_{j,n}^t, & n = 1, \cdots N; \\ \sum_{j=1}^{J} z_j = 1, & J = 1, \cdots J; \\ z_j \geq 0, & j = 1, \cdots J; \end{cases} \quad (1)$$

In equation (1), $P^t(x^t)$ is required to satisfy the standard

axioms of closed set, null-jointness, strong or free disposability, jointly weak disposability. z_j represents the observed value weight of each DMU (province). And if sum of the non-negative weight z_j equals 1, production returns to scale is variable. The DDF can be further defined as:

$$\vec{D}(x^t, y^t, b^t; -g_x, g_y, -g_b) = \sup\{\beta: (x^t - \beta g_x, y^t + \beta g_y, b^t - \beta g_b) \in P^t(x^t)\} \quad (2)$$

In equation (2), $g = (-g_x, g_y, -g_b)$ is the direction vector. β is a scalar, a bigger β implying a lower efficiency. When β is equal to 0, all DMUs (provinces) achieve the most efficient input and output. Based on the above DDF, environmental technical efficiency of pig production in China can be formulated as:

$$TE(x_j^t, y_j^t, b_j^t; g) = 1 - \vec{D}(x^t, y^t, b^t; -g_x, g_y, -g_b) \quad (3)$$

In accordance with Kuosmanen (2005)[17], let $\lambda_j = z_j + \mu_j$, carbon emission performance can be calculated by the following linear programming (LP):

$$\vec{D}(x, y, b; -g_x, g_y, -g_b) = Max\sigma \begin{cases} \sum_{j=1}^{J} z_j^t x_j^t \leq (1-\sigma)x_j^t \\ \sum_{j=1}^{J} z_j^t y_j^t \leq (1+\sigma)y_j^t \\ \sum_{j=1}^{J} (z_j + \mu_j^t) b_j^t \leq (1-\sigma)b_j^t \\ \sum_{j=1}^{J} (z_j + \mu_j) = 1 \\ z_j \geq 0, j = 1, \cdots, J \end{cases} (4)$$

In equation (4), b is undesirable output and y represents desirable outputs in pig production.

Let (x_t, y_t, b_t) and $(x_{t+1}, y_{t+1}, b_{t+1})$ be the input-output vector in period t and $t + 1$, $\vec{D}_0^t$ and $\vec{D}_0^{t+1}$ be the DDF in period t and $t + 1$ with reference to technology T in period t. Then the Malmquist Index of carbon emission performance based on DDF can be expressed as:

$$M^{t,t+1} = M_0(x_t, y_t, b_t, x_{t+1}, y_{t+1}, b_{t+1}) = \frac{\vec{D}_0^{t+1}(x_{t+1}, y_{t+1}, b_{t+1}; -g_x, g_y, -g_b)}{\vec{D}_0^t(x_t, y_t, b_t; -g_x, g_y, -g_b)} \quad (5)$$

2.2 Relevant variables and data Panel data from 2001 to 2012 for 30 provinces in China were utilized to measure regional carbon emission performance of pig production. To maintain statistical integrity, data for Chongqing, a municipality directly controlled by Central Government, were merged with data for Sichuan Province. Data for Hong Kong, Macau and Taiwan could not be accessed. In accordance with traditional zoning principles, the 30 provinces, municipalities and autonomous regions were divided into three areas: Eastern, Central and Western China. Eastern China includes 11 provinces (Beijing, Tianjin, Shanghai, Hebei, Liaoning, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan). Central China consists of 8 provinces (Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan). Western China comprises 11 provinces (Guangxi, Inner Mongolia, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang and Tibet). This data set is large enough to reflect the economic growth performance of pig production in national and

provincial China. Relevant variables were primarily derived from *China Rural Statistical Yearbook*, *Yearbook of China Livestock*, and *Chinese Agricultural Costs and Returns Compilation*. The input variables are labor, piglet, feed and other capital inputs. Labor was derived as annual slaughter multiplied by labor costs per accounting unit, mainly including family labor discount and employee fee; Piglets was described as annual slaughter multiplied by piglet costs per accounting unit; feed was derived as annual slaughter multiplied by total feed costs per accounting unit, including concentrated feed costs, green and coarse fodder costs, as well as feed processing costs. Other capital inputs were described as annual slaughter multiplied by capital costs per accounting unit, mainly including water and fuel coats, medical and epidemic prevention expenses, death loss charges, technical service fees, fixed assets depreciation expenses and period costs, etc. To eliminate the price changing effect, all the input variables were converted with the yearly agricultural production price index. The output

variables consist of desirable output and undesirable output. Desirable output was real GDP of pig production, which was converted into 2001 prices using a deflator. Undesirable output is carbon emission calculated for pig production, as recommended by IPCC. Livestock GHG emissions mainly derived from CH_4 produced by livestock enteric fermentation and CH4 and N_2O produced by manure[18]. To maintain statistical consistency, this study converted CH4 and N_2O into standard C. Hence, three pig production indices (CH_4 generated from pig enteric fermentation, CH4 generated from pig manure, and N_2O generated from pig manure) were used to determine carbon emissions according to

$$E = 6.8182E1_{CH_4} + 6.8182E2_{CH_4} + 81.2727E_{E_2O} \qquad (4)$$

where E is total pig production carbon emission, $E1_{CH_4}$, $E2_{CH_4}$ and E_{N_2O} are emissions of each index, derived as average annual feeding capacity multiplied by carbon emission coefficient. Carbon emission coefficients for the three carbon forms were taken from literature[4, 19].

Table 1 Pig production CEP for provinces in China from 2002 to 2012

Region	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Beijing	1.160	1.078	0.861	0.991	1.111	0.828	0.919	0.971	1.023	0.808	0.815
Tianjin	1.052	0.975	0.827	0.991	1.030	0.983	0.897	0.957	1.003	0.818	0.824
Hebei	1.124	0.960	0.834	0.989	1.043	0.942	0.919	0.971	1.038	0.814	0.823
Liaoning	1.036	0.962	0.738	0.985	1.084	0.531	0.921	0.971	0.971	0.824	0.840
Shanghai	1.103	1.011	1.875	0.456	1.054	0.806	0.890	0.978	1.017	0.812	0.823
Jiangsu	1.105	0.985	0.836	1.010	1.046	0.794	0.927	0.976	1.022	0.814	0.823
Zhejiang	1.091	0.960	0.818	1.022	1.038	0.772	0.907	0.979	1.021	0.813	0.826
Fujian	1.088	0.959	0.830	0.926	1.043	0.766	0.912	0.970	1.019	0.817	0.822
Shandong	1.089	0.978	0.835	0.972	1.095	0.811	0.924	0.971	1.019	0.819	0.822
Guangdong	1.102	1.006	0.840	0.974	1.057	0.781	0.925	0.973	1.017	0.813	0.823
Hainan	1.123	0.843	0.831	1.022	1.011	0.815	0.930	0.976	1.017	0.819	0.811
Heilongjiang	1.064	1.070	0.873	1.036	1.080	0.806	0.938	0.963	1.010	0.811	0.823
Jilin	1.296	0.953	0.922	1.038	1.036	0.808	0.919	0.981	1.002	0.814	0.817
Shanxi	1.098	1.034	0.881	0.995	1.018	0.798	0.954	0.951	1.023	0.815	0.817
Anhui	1.109	1.016	0.845	0.992	1.050	0.777	0.927	0.974	1.021	0.821	0.820
Jiangxi	1.134	1.051	0.814	1.007	1.029	0.733	0.924	0.971	1.020	0.813	0.822
Henan	1.069	0.970	0.836	0.994	1.037	0.837	0.924	0.973	1.019	0.817	0.820
Hubei	1.033	0.941	0.842	0.970	1.063	0.769	0.923	0.974	1.025	0.812	0.823
Hunan	1.109	0.974	0.849	1.015	1.054	0.826	0.932	0.967	1.017	0.816	0.822
Guangxi	1.174	1.089	0.902	0.971	1.050	0.766	0.926	0.972	1.022	0.817	0.823
Inner Mongolia	1.148	1.229	0.926	1.026	1.028	0.939	0.922	0.980	1.039	0.830	0.833
Shaanxi	1.124	1.018	0.794	1.049	1.105	0.710	0.936	0.982	1.018	0.819	0.822
Gansu	1.099	0.989	0.895	1.010	1.055	0.794	0.933	0.981	1.023	0.817	0.820
Ningxia	0.988	0.887	0.884	1.004	1.106	0.871	0.936	0.969	1.045	0.861	0.827
Qinghai	1.100	1.021	0.831	0.996	1.059	0.819	0.893	0.966	1.034	0.819	0.830
Xinjiang	0.974	0.904	0.779	0.927	1.074	1.037	0.900	0.982	1.023	0.822	0.741
Sichuan	1.134	1.044	0.864	0.992	1.051	0.806	0.920	0.965	1.018	0.820	0.826
Yunnan	1.074	0.990	0.839	1.013	1.047	0.784	0.930	0.981	1.020	0.816	0.824
Guizhou	1.113	0.977	0.911	0.994	1.060	0.755	0.925	0.988	1.024	0.814	0.828
Tibet	1.001	1.013	0.827	0.970	1.040	0.728	0.927	0.973	1.018	0.812	0.823
Mean	1.095	0.994	0.869	0.970	1.055	0.801	0.922	0.973	1.019	0.818	0.820

3 Empirical results

As pig production process is in line with VRS, hence the DEA model based on DDF in this study is also under VRS. Here we utilize the DEAP2.1 to calculate the pig production Malmquist carbon

emission performance (PMCEP) index in China, and decompose Malmquist index into technical efficiency change (EFFCH), technology change (TECHCH), "pure" technical efficiency change (PECH), and scale efficiency change (SECH). EFFCH refers to the DMU's ability to obtain the maximum output with given input, and it reflects the effective usage degree of existing technology in production process; TECHCH, *i. e.* technology progress, means improving productivity by improving existing technology; PECH means increasing productivity simply by improving the capacity of technology usage; SECH reflects whether the DMUs' production activity is on the most appropriate investment scale. Table 1 lists the pig production CEP results. From Table 1, we can see that the pig production CEP in various provinces showed periodic change from 2002 to 2012. The value in 2002, 2006 and 2010 was relatively high and there was a trend that the value decreased first and then increased, and the change trend in other province was basically same. Otherwise, the average pig production CEP in China also presented this trend.

    Further, we calculated the geometric mean of EFFCH, TH-CHCH, PECH, SECH and PMCEP of each province in China. The results are listed in Table 2 and Fig. 1. From a national perspective, average PMCEP during the 11-year period is 0.935, meaning that carbon emission performance of China's pig production has declined 6.5% on the average; average values of EFFCH, THCHCH, PECH and SECH are 1.007, 0.929, 1.002 and 1.004, hence inefficiency of technology progress is the main cause of PMCEP decline. From a regional perspective, PMCEP of Inner Mongolia, Jilin, Beijing and Guangxi has the minimum decreasing rate of 1.6%, 4.6%, 4.7% and 5.2%; PMCEP of Liaoning, Tibet, Fujian and Xinjiang has the maximum decreasing rate of 11.8%, 8.4%, 8.3% and 8.2%; as observed from Table 2 and Fig. 1, the PMCEP decline for all provinces is mainly caused by technology recession. Moreover, Table 2 revealed a technical inefficiency for Hainan, Xinjiang, Fujian, Hubei, Shanxi and Hebei, with an EFFCH declining rate of 2.0%, 2.0%, 1.8%, 1.6%, 0.4% and 0.1% respectively; except Hebei, technical inefficiency of the other 5 provinces is mainly caused by decline of "pure" technical efficiency.

Table 2   Mean value of EFFCH, THCHCH, PECH, SECH and PMCEP for each province in China

Region	Geometric Mean						Region	Geometric Mean					
	EFFCH	TECHCH	PECH	SECH	PMCEP	Rank		EFFCH	TECHCH	PECH	SECH	PMCEP	Rank
Beijing	1.011	0.943	1.012	0.999	0.953	3	Jiangxi	1.006	0.925	1.001	1.005	0.930	23
Tianjin	1.010	0.929	1.010	1.000	0.938	12	Henan	1.001	0.931	1.000	1.001	0.932	22
Hebei	0.999	0.947	1.000	0.999	0.946	6	Hubei	0.984	0.935	0.988	0.996	0.920	26
Liaoning	1.000	0.882	1.000	1.000	0.882	30	Hunan	1.016	0.924	0.999	1.018	0.939	11
Shanghai	1.011	0.925	1.013	0.998	0.935	15	Guangxi	1.011	0.938	1.011	0.999	0.948	4
Jiangsu	1.020	0.916	1.016	1.004	0.934	17	Inner Mongolia	1.015	0.970	1.010	1.005	0.984	1
Zhejiang	1.011	0.915	1.007	1.004	0.926	24	Shaanxi	1.007	0.928	1.004	1.002	0.934	19
Fujian	0.982	0.934	0.976	1.006	0.917	28	Gansu	1.021	0.922	1.022	0.999	0.942	8
Shandong	1.014	0.921	1.019	0.995	0.934	18	Ningxia	1.018	0.923	1.018	1.000	0.940	9
Guangdong	1.000	0.931	0.998	1.002	0.932	21	Qinghai	1.004	0.933	1.003	1.002	0.937	14
Hainan	0.980	0.940	0.981	0.999	0.921	25	Xinjiang	0.980	0.937	0.979	1.000	0.918	27
Heilongjiang	1.000	0.946	0.997	1.004	0.947	5	Sichuan	1.028	0.918	1.000	1.028	0.943	7
Jilin	1.003	0.951	0.998	1.005	0.954	2	Yunnan	1.007	0.926	1.005	1.002	0.933	20
Shanxi	0.996	0.942	0.994	1.003	0.939	10	Guizhou	1.013	0.927	1.009	1.004	0.938	13
Anhui	1.005	0.931	1.002	1.003	0.935	16	Tibet	1.045	0.876	1.000	1.045	0.916	29
China	1.007	0.929	1.002	1.004	0.935								
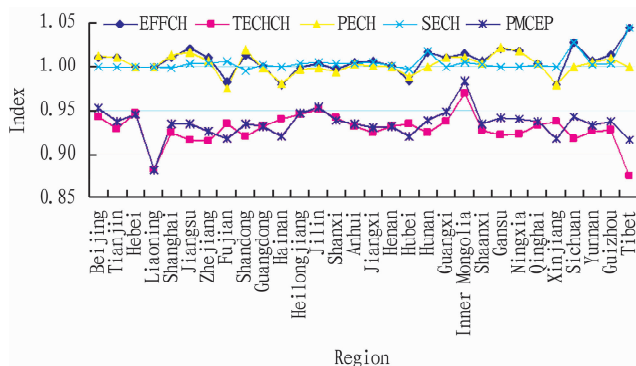
Fig. 1   Mean value of EFFCH, THCHCH, PECH, SECH and PMCEP for 30 provinces in China

    As shown in Fig. 2, Eastern China comprises 11 provinces, Central China, 8 provinces, Western China, 11 provinces. Thus there are 30 provinces in China. Fig. 2a shows the EFFCH changing tendency of Eastern China, Central China, Western China and the whole country. EFFCH of Eastern China was above 1 in 2005, 2007 and 2010, the other periods, below 1, showing a downward trend on the whole. For Central China and Western China, EFFCH fluctuated obviously during the sample period. In 2005, 2007, 2008 and 2010, technology efficiency in the whole country had an upward trend. Fig. 2b reveals a significant technology recession from 2007 to 2012 for all the three regions and the whole country. PECH of the three regions and the whole country was relatively stable during the sample period except for 2007. From 2002 to 2007, SECH of the three regions and China fluctuated obviously, while the SECH from 2008 to 2012 remained stable around 1. As to PMCEP in Fig. 2e, there were significant differences between the three regions and China before

2006, while the PMCEP converges in recent years. And among the three regions, Western China was ranked first for PMCEP, followed by Central China and Eastern China. This ranking is consistent with their livestock economic development.
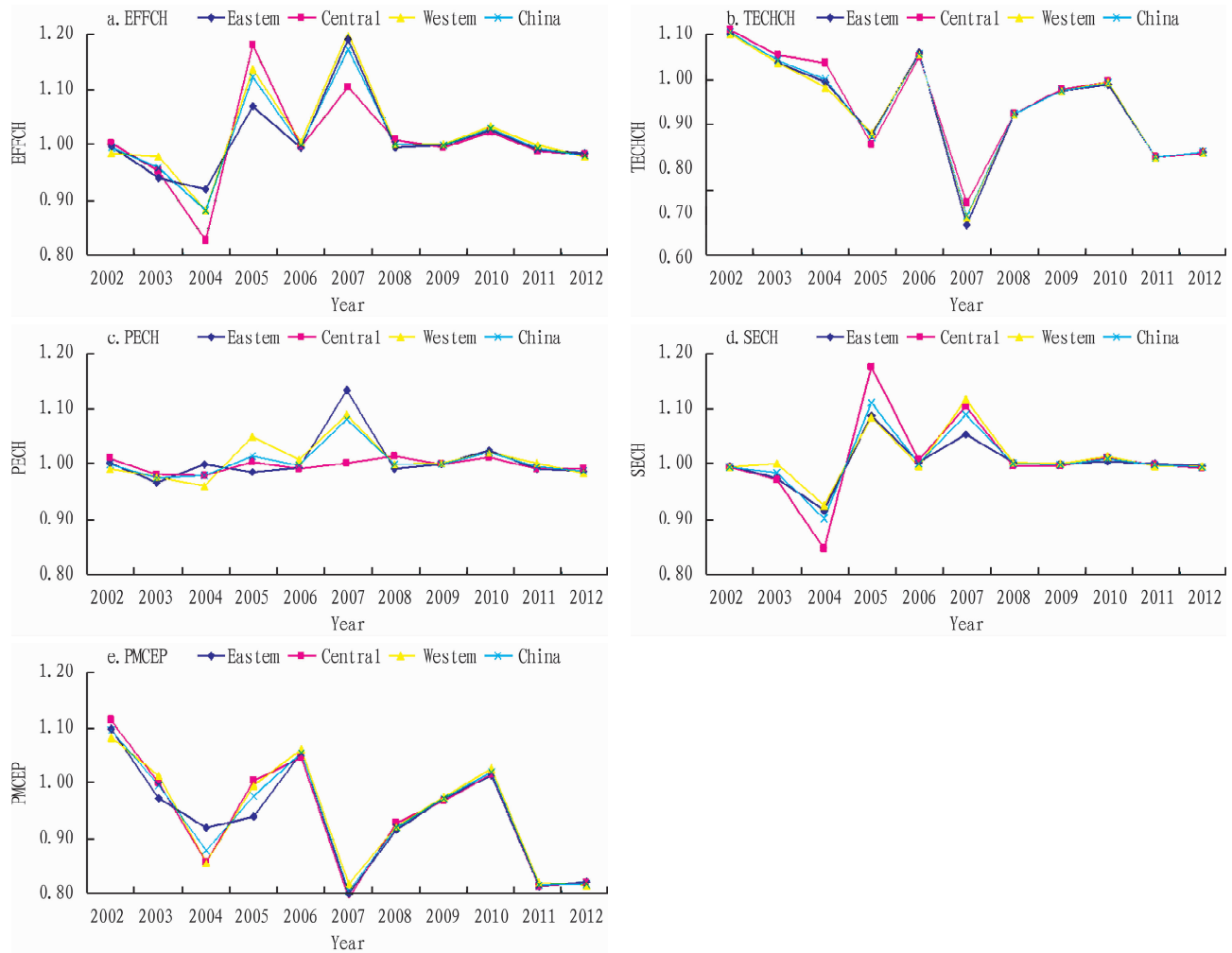
Fig. 2　EFFCH, THCHCH, PECH, SECH and PMCEP changing tendency in different areas

To further analyze whether the PMCEP is convergence or divergence, σ convergence test, absolute β test and conditional β test were conducted in the following section. Firstly, the σ convergence was measured by variation coefficient of regional PMCEP. Table 3 lists the testing results. For Eastern China and the whole country, variation coefficient of the corresponding PMCEP fluctuated frequently from 2002 to 2008, while it stabilized after 2008. Moreover, Table 3 revealed a significant σ convergence trend for PMCEP variation coefficient of Central and Western China during the sample period except 2007.

Table 3　Variation coefficient of regional PMCEP from 2002 to 2012

Region	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Eastern	0.010	0.032	1.099	0.282	0.008	0.161	0.002	0.000	0.003	0.000	0.001
Central	0.040	0.016	0.009	0.004	0.003	0.010	0.001	0.001	0.000	0.000	0.000
Western	0.042	0.082	0.028	0.010	0.006	0.114	0.002	0.001	0.001	0.002	0.008
China	0.106	0.140	1.070	0.304	0.019	0.234	0.005	0.002	0.005	0.002	0.007

Secondly, the approach of Sala-i-Martin (1996)[20] was utilized to test the absolute β convergence or divergence of PMCEP according to the formula:

$$(\ln PMCEP_{i,t} - \ln PMCEP_{i,0})/T = \alpha + \beta \ln PMCEP_{i,0} + \varepsilon_{i,t} \quad (6)$$

where $\ln PMCEP_{i,t}$ and $\ln PMCEP_{i,0}$ are the natural log of $PMCEP$ at time t and at the start time respectively, and T is the time span. α is a constant, β the convergence parameter to be estimated, and $\varepsilon_{i,t}$ represents the random error. $\beta > 0$ corresponds to a divergence trend and $\beta < 0$ to a convergence trend for the inter-regional PMCEP. Formula (6) was regressed by Ordinary Least Squares (OLS) method, and the results are shown in Table 4. As the esti-

mated β of Central China, Western China and China as a whole are negative at the significance level of 1%, there exists absolute β convergence for these regions. At the same time, since PMCEP of Central China, Western China and China as a whole showed a significant σ convergence trend (Table 3), it can be inferred that

PMCEP of these regions has all the characteristics of club convergence. The estimated β of Eastern China is negative, but it isn't significant, which means that PMCEP of this region doesn't have absolute β convergence trend. The above absolute β convergence test results are roughly consistent with the σ convergence test.

Table 4 Absolute β test of regional PMCEP

	Eastern China	Central China	Western China	China
C	-0.0345^*	-0.0177^*	-0.0244^{***}	-0.0241^{***}
	(0.0194)	(0.0100)	(0.0061)	(0.0057)
β	-0.1430	-0.2843^{***}	-0.1731^{***}	-0.2204^{***}
	(0.2001)	(0.0797)	(0.0613)	(0.0539)
$Adj\text{-}R^2$	-0.0045	0.1293	0.0602	0.0500
F	0.5104	12.7269^{***}	7.9790^{***}	16.7484^{***}
D. W	1.4860	0.8668	0.7803	1.2465

Note: The figures in brackets represent the standard error (SE) of the corresponding coefficient; * and *** denote the significance level of 10% and 1%, respectively.

Finally, the approach of Miller and Upadhyay (2002)[21] was used to test the conditional β convergence or divergence of PMCEP according to the formula

$$\ln PMCEP_{i,t} - \ln PMCEP_{i,t-1} = \alpha_i + b_t + \beta \ln PMCEP_{i,t-1} + \varepsilon_{i,t} \quad (7)$$

where α_i represents the steady level of the i-th region, and b_t is the time effect. Formula (7) was regressed by the panel data Fixed-Effect Model (FEM), and the results are shown in Table 5. As observed from Table 5, estimated β of the three regions and China

as a whole are negative at the significance level of 1%. Hence, PMCEP of the corresponding regions converges to their respective steady levels. Further, PMCEP of Central China, Western China and the whole country are in line with both absolute β convergence and conditional β convergence. Consequently, their provincial PMCEP is tending to a common steady-state level. For Eastern China, the estimated β of absolute β convergence test isn't significant, implying that PMCEP of each province is converging to different steady levels.

Table 5 Conditional β test of regional PMCEP

	Eastern China	Central China	Western China	China
C	-0.1048^{***}	-0.0818^{***}	-0.0738^{***}	-0.0887^{***}
	(0.0149)	(0.0128)	(0.0115)	(0.0077)
β	-1.2321^{***}	-0.9887^{***}	-0.9370^{***}	-1.0990^{***}
	(0.0903)	(0.1051)	(0.0946)	(0.0556)
$Adj\text{-}R^2$	0.6293	0.5257	0.4711	0.5660
F	186.0688^{***}	88.5545^{***}	98.0724^{***}	390.8873^{***}
D. W	1.3784	0.3442	0.5923	0.9096

Note: The figures in brackets represent the standard error (SE) of the corresponding coefficient, and *** denotes the significance level of 1%.

4 Conclusions

A DEA model based on Directional Distance Function was utilized to construct a model for calculating carbon emission performance of pig production. For pig production, real GDP is taken as the desirable output, carbon emission as the undesirable output, and labor, piglet, feed and other capital are input variables. The results show that the PMCEP for various regions and provinces in China fluctuated from 2001 to 2012. The national PMCEP had an average declining rate of 6.5%, which was mainly caused by inefficiency of technology progress. Among the three regions, Western China was ranked first for PMCEP, followed by Central China and Eastern China. This ranking is consistent with their livestock economic development. Convergence testing reveals a convergence trend for PMCEP both nationally and for the three economic regions. This indicates that differences in PMCEP among the regions are becoming smaller. In accordance with the study results, several recommendations are put forward. Firstly, the DEA model includes other

influencing factors for measurement of PMCEP, except real GDP, carbon emission, labor, piglet, feed and other capital inputs. Governments are advised to introduce a newly-established model to evaluate regional carbon emission status, thereby proposing effective carbon emission reduction measures. Secondly, the technology progress shows an overall downward trend and even reverse trend, while the other three factors of PMCEP are at a high level as a whole, indicating that introduction of new technology is very necessary. Specialized training institutions need to be set up in various areas to promote science and technology usage in pig production.

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provide high-yield seed to farmers via scientific breeding and improve farmland's insect prevention ability via technology channel, thereby guaranteeing the stability and improvement of grain yield per unit area. (ⅲ) Strictly control the number of cultivated land and guarantee per capita cultivated land area. At present, China is just at high-speed development period of urbanization. When urbanization rate is quickly improved, it should notice to protect the area and quality of cultivated land. Government should strictly control the implementation process of farmland "occupying one and supplementing one" policy, and unify quantity and quality.

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