Measurement and convergence of carbon productivity across Shanghai's manufacturing sectors

Runong Xu
Department of Business, East China University of Science and Technology, Shanghai China and Department of International Business, Zhejiang Yuexiu University of Foreign Languages, Shaoxing, China

Yuming Wu
Department of Business, East China University of Science and Technology, Shanghai, China, and

Yao Huang
Department of International Business, Zhejiang Yuexiu University of Foreign Languages, Shaoxing, China

Received 17 November 2019
Revised 21 February 2020
Accepted 18 March 2020

Abstract

Purpose – Increasing carbon productivity is an effective way to reduce carbon emissions, while boosting economic prosperity. For appropriate formulating and enforcement of energy saving and carbon emissions reduction policies in various sectors, it is of great significance to investigate the evolution characteristics and convergence modes of carbon productivity across the manufacturing sectors.

Design/methodology/approach – Using slack-based measure directional distance function (SBM-DDF) and global Malmquist–Luenberger (GML) productivity index, this paper measures the carbon productivities of 29 manufacturing subsectors in Shanghai, China, from 2001 to 2016 under the total factor framework. Furthermore, based on the convergence theories, it empirically examines the convergence of carbon productivity across these manufacturing sectors.

Findings – The measurement results suggest that the carbon productivities of the manufacturing sectors in Shanghai show an increasing tendency on the whole, and technical efficiency instead of technological change makes a main contribution to the increase. It is found that there is no obvious σ convergence across the manufacturing sectors in Shanghai, but there exist both absolute β convergence and conditional β convergence. Moreover, there is heterogeneity in convergence characteristics between the clean sectors and polluting sectors. The findings also show that firm size and industry structure have significant positive impacts on the growth of carbon productivities of the manufacturing sectors, whereas the impacts of capital deepening and energy consumption structure are significantly negative.

International Journal of Climate Change Strategies and Management
Vol. 12 No. 3, 2020
pp. 369-387
Emerald Publishing Limited
1756-8692
DOI 10.1108/IJCCSM-11-2019-0065

Originality/value – This paper measures the carbon productivities of the manufacturing subsectors by applying SBM-DDF and GML index, so as to improve the accuracy. It provides an insight into the convergence of carbon productivity across the manufacturing sectors.

Keywords Measurement, Absolute β; convergence, Carbon productivity, Conditional β convergence, σ Convergence

Paper type Research paper

1. Introduction

Climate change poses a severe threat to human development. It has already been recognized that the key to addressing climate change is to reduce carbon dioxide (CO_2) emissions. Governments all over the world are making remarkable efforts to reduce fossil fuel use and carbon emissions. As the world's largest greenhouse gas emitter, China has made a commitment on reducing CO_2 emissions intensity by 40%–45% in comparison with the 2005 level and raising the percentage of non-fossil energy in primary energy consumption to 15% by 2020. A commitment has also been made by the Chinese authority on reaching the peak carbon emissions around 2030. Carbon emissions come mainly from economic activities, especially in the manufacturing process. From 1995 to 2015, the CO_2 emissions of China's manufacturing industries increased by about 220.77% and accounted for 58.27% of the national total CO_2 emissions (Liu *et al.*, 2019). Obviously, improving energy efficiency and reducing CO_2 emissions in the manufacturing sector is crucial to achieving China's peak emission targets. Carbon productivity reflects the efficiency of CO_2 emissions in economic development, which is a key indicator that can combine economic growth with CO_2 emissions (Mielnik and Goldemberg, 1999). Unless developing countries find other integrated economic/environmental solutions, their per capita emissions will continue to increase during development (Cutlip and Fath, 2012). Therefore, increasing carbon productivity is an effective way to reduce carbon emissions, while boosting economic prosperity in Chinese manufacturing industries. Owing to different characteristics and production processes, the carbon productivity varies from sector to sector. Therefore, for the purpose of appropriate formulation and enforcement of energy saving and carbon emissions reduction policies in various sectors, it is of great significance to investigate the evolution characteristics and convergence modes of carbon productivity across the manufacturing sectors.

There have been a lot of studies on environmental issues considering CO_2 emissions. First, with respect to the measuring methods of the environmentally sensitive productivity growth, Malmquist–Luenberger (ML) index proposed by Chung *et al.* (1997) has been widely used in previous studies, though, the ML index may have the infeasibility problem. Oh (2010) resolved the problem by defining the global production possibility set (PPS) and constructed the global Malmquist–Luenberge (GML) index. Although the biennial Malmquist–Luenberge (BML) index proposed by Pastor *et al.* (2011) avoids linear programming infeasibilities but compared with the GML index, it lacks transitivity. Besides, to the best of our knowledge, concerning the measurement of total factor carbon productivity, most studies use radial DEA method without considering slack in the constraints, which can be biased. Second, with respect to the convergence analysis, according to what we know, the previous studies usually focus on the convergence of CO_2 emissions and carbon intensity, while there are only a limited number of studies specifically dealing with carbon productivity convergence. Moreover, most of these convergence studies concentrate on the regional differences, for instance, provincial and prefecture-level differences, whereas few are related to the differences of sector levels. Previous studies have laid the foundation for further research. The contributions and main innovations of this study are as follows: first, this paper attempts to measure carbon productivities of 29 manufacturing subsectors in Shanghai applying slacks-based measure directional distance function (SBM-DDF) and GML index, so as to improve the accuracy and efficiency of the calculation. Second, from the perspective of manufacturing subsectors, rather than at the geographical level, it provides an insight into the convergence of carbon productivity across the manufacturing subsectors in Shanghai for the first time.

Manufacturing industry is the foundation of economic development and an important indicator of comprehensive economic strength in a nation or region and is also a crucial part of the real economy. Owing to a distinctive combination of factors, Shanghai has been China's leading industrial and manufacturing center for some time. Its manufacturing industry has always been an essential part of the city's economy. According to statistics, the added value of Shanghai's manufacturing industry accounted for 26% of the city's GDP in 2016. Additionally, Shanghai's 13th Five-Year Plan set a new target, i.e. the ratio of the manufacturing added value to the city's GDP would be about 25% with its best efforts. However, the "extensive" development of Shanghai's manufacturing industry has also resulted in a considerable amount of energy consumption and CO_2 emissions, which hinder the promotion of sustainable economic growth. Furthermore, Shanghai's manufacturing industry is facing downward pressure with an increasing phenomenon of "industry hollowing out." The annual carbon emissions of Shanghai's manufacturing industry rose from 36.94MT in 2001 to 52.4 MT in 2016, at an average growth rate of 2.36% on a year to year basis, which made a severe test to the sustainable development of the industry. Shanghai municipal Government successively made "Shanghai's 13th Five-Year Plan for Industrial Green Development" and "Shanghai's 13th Five-Year Plan for Transformation and Upgrading of Manufacturing" in February 2016 and June 2017, respectively, emphasizing the concept of green development and set the goal of reducing the energy consumption per value added of firms above designated size by about 15% in 2020 compared to 2015 levels. The city also committed to peak CO_2 emissions by around 2025, which put new pressure on the green development of the manufacturing industry. Thus, under the dual constraints of resource and environment, improving the carbon productivity of the manufacturing industry is essential to the sustainable development of Shanghai.

The remaining of the paper is structured as follows. In Section 2, we concentrate on the measures of sectoral carbon productivity and method for convergence analysis. In Section 3, data source and processing are reported. In Section 4, the changing trends of carbon productivity across the manufacturing sectors are analyzed. Moreover, we present a convergence analysis of carbon productivity across manufacturing sectors in Shanghai, with the derived empirical results being presented and discussed. In Section 5, we conclude the study and provide some policy implications.

2. Methodology and theories

2.1 Measurement method for carbon productivity

There are many studies on measuring environmental efficiency and productivity, in which the DEA method has received more and more scholarly attention. For example, Kumar and Jain (2019) used the Luenberger productivity indicator to evaluate the carbon-sensitive productivity of 56 Indian thermal power plants during the period of 2000–2013. Previous studies usually use the Malmquist (M) index method to measure total factor productivity (TFP) (Zhou *et al.*, 2010; Zhang *et al.*, 2015; Yang *et al.*, 2015; Yang and Wang, 2016; Sueyoshi *et al.*, 2017). Nevertheless, the traditional M index does not take into account the "bad output" such as waste water, exhaust gas and CO_2 that may exist in the production process, but in reality CO_2 often exists in the form of undesired output, so this may lead to bias in environmental productivity measures. To solve this problem, Chung *et al.* (1997) constructed a new productivity index on the basis of the geometrics mean of DDF, namely, the ML index, which considered both the desired output and the undesired output. Later, the ML index has been widely used to measure productivity (Watanabe and Tanaka, 2007; Wang *et al.*, 2013; Arabi *et al.*, 2015; Chen, 2016; Aghayi and Maleki, 2016). However, the ML index still has some weakness, and there may be cases where linear programming has no solutions, which makes the measuring results lack stability or be inconsistent with actual production activities. Färe *et al.* (2001) demonstrated the infeasibility problem intuitively. To overcome this weakness, Tone (2001) developed a slacks-based DEA model, and Fukuyama and Weber (2009) and Färe and Grosskopf (2010) suggested a more generalized SBM-DDF. In addition, Oh (2010) presented a global PPS when measuring the TFP and proposed the GML index. This productivity index is circular without the potential infeasibility issue and its application in the research studies of environmentally sensitive productivity growth began in recent year (Ananda and Hampf, 2015; Tao *et al.*, 2017; Chen *et al.*, 2018). Besides, to avoid the problem of linear programming infeasibilities, Pastor *et al.* (2011) proposed the biennial Malmquist productivity (BM) index. Based on the BM index, the BML index was constructed to measure the productivity (Zhao and Lin, 2019), however compared to the GML index, the BML index lacks transitivity.

Here, we present the methodology of SBM-DDF and GML index.

2.1.1 Global production possibility set. The decision-making unit (DMU) consists of various Shanghai's manufacturing subsectors and a total of 29 DMUs are included, DMU_k ($k = 1, 2, \cdots, K$). According to Färe *et al.* (2007), the production technology for each manufacturing sector produces N desirable outputs, $y = (y_1, \cdots, y_N) \in R_N^+$ and I undesirable outputs, $b = (b_1, \cdots, b_I) \in R_I^+$ by using M inputs, $x = (x_1, \cdots, x_M) \in R_M^+$. The set $(x^{k,t}, y^{k,t}, b^{k,t})$ represents the inputs and outputs of sector k in period t. $P(x)$ denotes the PPS, which satisfies the following assumptions: closed sets, the strong disposability of inputs, the weak disposability of undesirable outputs, and undesirable outputs are inseparable from desirable outputs. Using the DEA method, the contemporaneous PPS can be expressed as follows:

$$P^t(x) = \left\{ \left(y^t, b^t\right) : \sum_{t=1}^{T} \sum_{k=1}^{K} z_k^t y_{kn}^t \geq y_{kn}^t, \forall n; \sum_{t=1}^{T} \sum_{k=1}^{K} z_k^t b_{ki}^t = b_{ki}^t, \forall i; \ \sum_{k=1}^{K} z_k^t = 1, z_k^t \geq 0, \forall k \right\} \tag{1}$$

where z_k^t represents the weight of each cross-section observation, and the constraint $\sum_{k=1}^{K} z_k^t = 1, z_k^t \geq 0$ means that the production technology exhibits variant returns to scale.

Based on the global PPS constructed by Oh (2010), the GML index needs to replace the contemporaneous PPS, $P^t(x^t)$ with a global PPS, $P^G(x)$, where $P^G(x) = P^1(x^1) \cup P^2(x^2) \cup [\ldots] \cup P^T(x^T)$, meaning that the global reference production set is the sum of that of all the periods. As shown in Figure 1, the global benchmark technology equals to the envelopment of all the T contemporaneous benchmark technologies. $P^G(x)$ extends the method of Pastor and Lovell (2007) by considering unintended outputs in production process. $P^G(x)$ can be formulated as follows:

$$P^G(x) = \left\{ \left(y^t, b^t\right) : \sum_{t=1}^{T} \sum_{k=1}^{K} z_k^t y_{kn}^t \geq y_{kn}^t, \forall n; \sum_{t=1}^{T} \sum_{k=1}^{K} z_k^t b_{ki}^t = b_{ki}^t, \forall i; \right.$$
$$\left. \sum_{t=1}^{T} \sum_{k=1}^{K} z_k^t x_{km}^t \leq x_{km}^t, \forall m; \sum_{k=1}^{K} z_k^t = 1, z_k^t \geq 0, \forall k \right\} \tag{2}$$

2.1.2 Global slack-based measure directional distance function. The DDF has many favorable features, but it does not consider slacks in the constraints when estimated applying DEA, which are important sources of inefficiency (Fukuyama and Weber, 2009). Hence, we use the SBM-DDF developed by Fukuyama and Weber (2009) in this paper. Incorporating CO_2 as an undesired output, the function is defined as:

$$P^t(x) = \left\{ \left(y^t, b^t\right) : \sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t y_{kn}^t \geq y_{kn}^t, \forall n; \ \sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t b_{ki}^t = b_{ki}^t, \forall i; \ \sum_{k=1}^{K} z_k^t = 1, z_k^t \geq 0, \forall k \right\} \tag{3}$$

where the SBM-DDF, S_V^G is defined on the global PPS, $P^G(x)$. $x^{t,k'}$, $y^{t,k'}$ and $b^{t,k'}$ are the input and output vectors of the sector k in period t and g^x, g^y as well as g^b are directional vectors, which indicate the decrease of input and the increase (decrease) of desirable output (undesirable output) . s_m^x, s_n^y and s_i^b represent the slack in the input, desirable output and undesirable output constraints, respectively. s_m^x and s_i^b being positive indicate that production is not at the technology frontier and the actual inputs and pollution exceed that of the boundary, whereas S_n^y being positive implies that the actual outputs are insufficient.

2.1.3 Global Malmquist–Luenberger index. On the basis of global SBM-DDF, this paper further constructs the GML index to measure the carbon productivities of the Shanghai's manufacturing sectors. GML index can solve the potential infeasibility problem. Referring to the idea of Oh (2010), the index is defined as follows:

$$GML_t^{t+1} = \frac{1 + S_V^G\left(x^t, y^t, b^t; g\right)}{1 + S_V^G\left(x^{t+1}, y^{t+1}, b^{t+1}; g\right)} \tag{4}$$

In this study, we measure the carbon productivity growth by calculating the change of GML from time t to $t+1$. $GML_t^{t+1} > (<) 1$ corresponds to productivity gain (loss). Specifically, a GML_t^{t+1} index greater than 1 indicates that the carbon productivity is rising from time t to $t+1$, whereas a GML_t^{t+1} index less than 1 shows that the carbon productivity is decreasing from time t to $t+1$ and $GML_t^{t+1} = 1$ implies that the carbon productivity is the same between the two periods. TheGML_t^{t+1} index can be further decomposed into the efficiency change (GEC_t^{t+1}) and the technical change (GTC_t^{t+1}), specifically decomposed as follows:

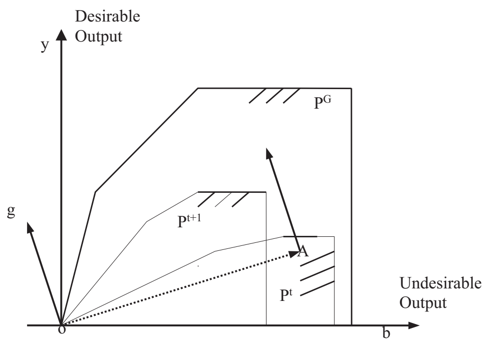

Figure 1.
GML productivity index

$$
\begin{aligned}
GML_t^{t+1} &= GEC_t^{t+1} \times GTC_t^{t+1}, \\
GEC_t^{t+1} &= \frac{1 + S_V^t\left(x^t, y^t, b^t; g\right)}{1 + S_V^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; g\right)}, \\
GTC_t^{t+1} &= \frac{\left[1 + S_V^G\left(x^t, y^t, b^t; g\right)\right] / \left[1 + S_V^t\left(x^t, y^t, b^t; g\right)\right]}{\left[1 + S_V^G\left(x^{t+1}, y^{t+1}, b^{t+1}; g\right)\right] / \left[1 + S_V^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; g\right)\right]}.
\end{aligned}
\tag{5}
$$

where $GEC_t^{t+1} > (<)1$ corresponds to the efficiency improvement (degradation) of carbon productivity. $GTC_t^{t+1} > (<)1$ indicates a movement in the global technology frontier toward increasing (decreasing) desirable outputs and decreasing (increasing) undesirable ones.

2.2 Convergence hypothesis and test

With the increasing global warming threat, a rising number of literatures have investigated the evolution and convergence of CO_2 emissions and energy productivity recently. Mulder and De Groot (2012) found that the cross-country differences in overall energy intensity tended to decline through an examination on the energy intensity across 18 OECD nations between 1970 and 2005, and the lagging countries were inclined to catch up with leading countries, with the average convergence rate of the service industry being higher than that of the manufacturing industry. Similar studies were conducted by Liddle (2009, 2010) and Wana *et al.* (2015). Herrerias (2012) investigated the per capita CO_2 convergence across 25 EU countries from 1920 to 2007 and confirmed the convergence hypothesis among them.

For the effective allocation of China's target to cut emissions across regions, the convergence of CO_2 emissions and carbon intensity have been researched in some studies. For instance, Huang and Meng (2013) empirically concluded that per person carbon emissions in the urban area of China exhibited convergence between 1985 and 2008, considering the spatial effects. Wang and Zhang (2014) tested the convergence of carbon emissions per person in six sectors of 28 provinces between 1996 and 2010, finding strong evidence of convergence across provinces. Yang *et al.* (2016) conducted similar provincial convergence research using GMM estimator. Additionally, using a continuous dynamic distribution method, Wu *et al.* (2016) found the existence of convergence of the per person CO_2 emissions across 286 Chinese cities between 2002 and 2011. Furthermore, exploratory research has been conducted by some researchers on carbon intensity convergence in China. For example, Hao *et al.* (2015) concluded that there existed stochastic convergence as well as β convergence in carbon intensity across 29 Chinese provinces from 1995 to 2011. Zhao *et al.* (2015) verified the convergence hypothesis in CO_2 intensity among provinces in China between 1990 and 2010 using dynamic spatial model. Li *et al.* (2017) claimed that carbon intensity presented stochastic convergence across cities in the Yangtze River Delta from 2000 to 2010 and there was β-convergence by applying spatial panel data models. However, there are only a limited number of studies concerning carbon productivity convergence. For example, Li and Song (2017) believed that the carbon productivity in China's inland and coastal regions would be converging as the gap of per capita GDP decreases and the shirking of the technological progress gap and human capital investment gap would accelerate the convergence. Bai *et al.* (2019) analyzed the convergence of total carbon productivity among 88 countries and regions in the world and found that there was no convergence in the whole sample, but there existed the club convergence.

Investigating the carbon productivity convergence of the manufacturing sectors in Shanghai is conductive to identifying carbon productivity trends and formulating specific emissions reduction policies. Because Shanghai is a province-level municipality, this study is focused on regional/provincial level. To determine the dynamic evolution trends of carbon productivities in different the manufacturing sectors in Shanghai in-depth, we empirically test the convergence hypothesis. Two main hypotheses of convergence are presented in the previous studies, namely σ convergence and β convergence. Moreover, referring to Sala-i-Matin (1996), the latter can be further divided into absolute β convergence and conditional β convergence.

2.2.1 σ Convergence. There is σ convergence if the cross-sectional dispersion of carbon productivity across sectors has the tendency of decreasing significantly over time. Standard deviation and coefficient of variation, measures of variability, are used here to study the σ convergence of carbon productivity across the manufacturing sectors in Shanghai. The specific calculation formula is given as:

$$S = \sqrt{\frac{\sum_{i=1}^{N}(\mathrm{CP_{it}} - \overline{\mathrm{CP_{it}}})}{N}};\ \mathrm{CV} = S/\overline{\mathrm{CP}}_t \tag{6}$$

where N denotes the number of manufacturing sectors and S denotes the standard deviation. CP_{it} is the carbon productivity of sector i in year t, $\overline{CP}_t$ represents the average value of carbon productivity in year t and CV denotes the coefficient of variation.

2.2.2 Absolute β convergence. The absolute β convergence hypothesis based on neoclassical growth theory implies that the growth rates of poor economies are higher than those of the rich ones and all the economies approach the common steady state in the long term. For this data set, absolute β convergence examines whether carbon productivities in sectors with lower initial levels have the tendency of growing faster than those in the sectors with higher initial levels. There is absolute β convergence if the carbon productivities of different sectors are converging to one another irrelevantly of their initial conditions. Referring to Sala-i-Matin (1996), the empirical specification of our model is given as:

$$g_{i,t} = \alpha + \beta \ln CP_{i,t-1} + \eta_i + \gamma_t + \varepsilon_{i,t} \tag{7}$$

where $\ln CP_{i,\ t-1}$ is the logarithmic form of carbon productivity of sector i in year $t-1$, $g_{i,t}$ indicates the growth rate of carbon productivity of sector i in year t, i.e. $g_{i,t} = (\ln CP_{i,t} - \ln CP_{i,0})/t$ and $\ln CP_{i,0}$ refers to the carbon productivity in the base period, $t \in [1, 14]$. α is the intercept terms; η_i, γ_i and $\varepsilon_{i,t}$ are the individual fixed effects reflecting the sector heterogeneity, time fixed effects, and random disturbance terms, respectively. The coefficient β is the parameter of our central interest. A significant negative β indicates the presence of absolute β convergence of carbon productivity across the manufacturing sectors in Shanghai.

2.2.3 Conditional β convergence. Also, according to neoclassical growth theory, the conditional β convergence hypothesis indicates that economies with identical structural characteristics approach the common steady state in the long term irrespective of their initial levels. In conditional β convergence, if different manufacturing sectors have different structural characteristics, e.g. firm size and energy consumption structure, then they will have different steady states over time. Conditional β convergence model is developed by incorporating several control variables that may affect the convergence of carbon productivity of the absolute β convergence model. Referring to the previous literature, the conditional β convergence model is established as follows:

$$g_{i,t} = \alpha + \beta_1 \ln CP_{i,t-1} + \beta_2 ES_{i,t} + \beta_3 IS_{i,t} + \beta_4 KL_{i,t} + \beta_5 RS_{i,t} + \eta_i + \gamma_t + \varepsilon_{i,t} \quad (8)$$

In this model, $ES_{i,t}$ denotes the firm size of sector i in period t, represented by the increase rate of the ratio of industrial output value (IOV) to the number of enterprise above designated size of the sector. $IS_{i,t}$ denotes the industrial structure of sector i in period t, which is represented by the ratio of IOV of the sector to that of the overall manufacturing industry. When the industry's focus is on sectors with high carbon productivity, the structural effect is positive and vice versa. $KL_{i,t}$ denotes the degree of capital deepening of each sector in period t, computed by the ratio of its capital to labor. $RS_{i,t}$ denotes the energy consumption structure of each sector, represented by the ratio of the consumption of coal energy to total energy consumption. Coal is a kind of energy source with high emissions coefficient. Cheap coal with abundant reserve is a preferred element (Pan *et al.*, 2019). In Shanghai, coal is the largest fossil fuel source of its industrial CO_2 emissions with a proportion of more than 50% from 1994 to 2011 (Shao *et al.*, 2011), hence sectors having different energy consumption structure may also have difference in carbon productivities. The coefficients for each control variable, i.e. firm size, industry structure, capital deepening and energy consumption structure are indicated by β_2–β_5, respectively. Other variables in the equation (8) are the same as those in the equation (7).

2.3 Estimation method

Concerning the estimation method, for the absolute convergence β model, we use the panel data methods based on Hausman test. Because of the incorporation of the control variables that affect the growth of carbon productivity, the conditional β convergence model may have endogenous problems caused by missing explanatory variables. To solve this problem, the usual practice of the existing literature is to use the first-order differential GMM estimator or system GMM estimator. Considering that differential GMM has a weak instrumental variable problem, we apply the system GMM approach to estimating the conditional β convergence model. Whether the system GMM estimator is consistent is decided by the instrument validity and the no serial correlation assumption, which can be tested by two specification tests, i.e. a Sargan test for the exogeneity of subsets of the instruments and an Arellano–Bond test for serial correlation.

3. Data

There are 31 two-digit manufacturing sectors in total according to China's Classification of National Economy Industry (GB/T4754-2011). Because of the incompleteness of data, we remove two sectors from our data set [1]. For the consistency of statistical caliber, referring to Li *et al.* (2018), we split the sector "Rubber and Plastics Products" into two sectors: "Rubber Products" and "Plastics Products". Moreover, the "Manufacture of Automobiles" and "Manufacture of Railway, Ship, Aerospace, and Other Transport Equipment" are merged into "Transport Equipment". Thus, we collect the data of 29 manufacturing subsectors [2] in Shanghai from 2001 to 2016. The variables are selected as follows:

3.1 Inputs

Capital, labor and energy are selected as inputs of production activities. The input data are obtained from the Shanghai Statistical Yearbook 2002–2017. The annual average number of employees of different manufacturing subsector is chosen as an indicator of the labor. Aggregate energy consumption of each manufacturing subsector is adopted to indicate energy, measured by 10,000 tons of standard coal. Capital investment is estimated using the perpetual inventory method at constant prices in 2000:

$$K_{i,t} = (1 - \delta_{i,t})K_{i,t-1} + I_{i,t} \tag{9}$$

where $I_{i,t}$ is the amount of fixed asset investment in different manufacturing sectors in year t, $K_{i,t}$ and $K_{i,t-1}$ are the capital stock of different manufacturing sectors in year t and $t-1$, respectively, $K_{i,0}$ is the initial value for K in the base year (i.e. year 2000 in this study) and $\delta_{i,t}$ is the depreciation rate of capital stock. Referring to Zhang *et al.* (2004), $\delta_{i,t}$ is assumed to be 9.6%. Moreover, $K_{i,0}$ is determined using the steady-state method proposed by Harberger (1978). Here is the estimation formula:

$$K_{i,t-1} = I_{i,t}/\,(g_{i,t} + \delta_{i,t}) \tag{10}$$

where $g_{i,t}$ refers to the average annual growth rate of output during the studied period, which is represented by the geometric average growth rate of industrial output of Shanghai's manufacturing sectors from 2001 to 2016.

3.2 Desirable output

The total IOV of each manufacturing sub-sector in Shanghai is selected to measure the desirable outputs. The total IOV data is collected from the Shanghai Statistical Yearbook 2002–2017 and is converted into the 2,000 constant prices using the industrial producer price index of Shanghai obtained from China Statistical Yearbook.

3.3 Undesirable output

Industrial CO_2 emissions are selected as the proxy of the undesirable output. As the CO_2 data is not available, we estimate it in terms of the total consumption of various energy types. According to IPCC (2006), CO_2 emissions from various manufacturing sectors can be calculated by the following formula:

$$CO_2 = \sum_{i=1}^{8} CO_{2,i} = \sum_{i=1}^{8} E_i \times NCV_i \times CEF_i \times COF_i \times \frac{44}{12} \tag{11}$$

where i represents the energy types, E_i represents the adjusted energy consumption, NCV_i, CEF_i and COF_i refer to the net calorific value, carbon content and the oxygenation efficiency of various energy types, respectively (Table 1). From NCV_i, CEF_i and COF_i, the emission factors for various fossil fuels can be calculated, i.e. it is the product of these three. Table 1 also reports the emission factors for the selected major fossil fuels. The values of 44 and 12 refer to the molecular weights of CO_2 and carbon, respectively. Table 2 displays the descriptive statistics of variables adopted here.

4. Results and discussion

4.1 Measuring results and discussion

Table 3 reports the average carbon productivity of each manufacturing sector in Shanghai from 2002 to 2016 and its decompositions, i.e. the global efficiency change (GEC) and the global technological change (GET). As shown in Table 3, among the 29 sectors, the average carbon productivities of 21 sectors such as transportation equipment, electronic and telecommunications equipment as well as chemical fiber are greater than 1, and those of two sectors, namely, the papermaking and paper products as well as nonmetal mineral products are equal to 1, whereas those of the other six sectors are less than 1, e.g. leather and related products, smelting and pressing of nonferrous metals and furniture manufacturing. Obviously, the carbon productivities of the manufacturing sectors in Shanghai show an increasing tendency on the whole, and technical efficiency is the leading contributor to the growth, with GEC being greater than GET in most sectors. In some sectors, the negative growth of technological change even offsets the positive growth of technical efficiency.

The annual trends of carbon productivities of 29 sectors during the studied period are also analyzed. The temporal trends of ten representative sectors are depicted in Figure 2. It can be found that, first, the carbon productivities of most subsectors are greater than 1 and concentrate in the range of 0.9 to 1.2, but the carbon productivity of each subsector still exhibits strong heterogeneity. The top three sectors in terms of carbon productivity are the transportation equipment, chemical fiber and electronic and telecommunications equipment. The reason for this may be that these three sectors are the pillar sectors of Shanghai's manufacturing industry with relatively high technical efficiency and so the energy can be fully used. Second, according to the pollution degree, the 29 manufacturing sectors are divided into 10 polluting sectors and 19 clean sectors in this study [3]. From this classification, the volatility of carbon productivity in the clean sectors is small, e.g. metal products and ordinary machinery, whereas that in the polluting sectors is high, such as petroleum processing as well as smelting and pressing of nonferrous metals.

4.2 Empirical analysis of carbon productivity convergence

4.2.1 σ Convergence test. Figure 3 presents the trends in the coefficient of variation of carbon productivity in the overall manufacturing sectors, polluting sectors and clean sectors from 2002

Table 1.
Emission factors for different energy types

Factors	Raw coal	Coke	Crude oil	Gasoline	Kerosene	Diesel oil	Fuel oil	Nature gas
NCV_i	20,908	28,435	41,816	43,070	43,070	42,652	41,816	38,931
CEF_i	26.4	29.5	20.1	18.9	19.5	20.2	21.1	15.3
COF_i	0.94	0.93	0.98	0.98	0.98	0.98	0.98	0.99
Emission factor	0.5183	0.7801	0.8237	0.7978	0.8231	0.8443	0.8647	0.5897

Table 2.
Descriptive statistics of variables related to carbon productivity measurement

Variables		No. of observations	Mean	Std.	Min.	Max
IOV	Industrial output value (100m RMB)	464	759.79	1154.01	31.08	7107.48
CO_2	CO_2 emissions (10,000 tons)	464	147.90	463.21	0.08	3064.78
Labor	Average number of employees (10,000)	464	8.47	8.70	0.33	46.77
Capital	Capital stock (100m RMB)	464	173.78	286.40	4.76	2946.08
Energy	Total energy consumption (10,000 tons of SCE)	464	135.10	256.73	0.09	1570.48

Sectors	GML	GEC	GET
S1	1.003	1.023	0.980
S2	1.002	1.005	0.996
S3	1.001	0.965	1.038
S4	0.998	1.000	0.998
S5	1.001	1.046	0.957
S6	1.002	1.035	0.968
S7	0.980	1.000	0.980
S8	1.002	1.016	0.986
S9	0.994	0.979	1.015
S10	1.000	0.999	1.001
S11	0.999	0.990	1.010
S12	1.009	1.039	0.972
S13	1.033	1.051	0.983
S14	1.036	1.042	0.994
S15	1.002	1.025	0.978
S16	1.046	1.030	1.015
S17	1.001	0.966	1.036
S18	1.005	1.014	0.991
S19	1.000	1.028	0.973
S20	1.010	1.027	0.984
S21	0.988	1.000	0.988
S22	1.002	1.012	0.990
S23	1.012	1.021	0.990
S24	1.008	1.014	0.994
S25	1.047	1.047	1.000
S26	1.014	0.998	1.017
S27	1.044	1.040	1.004
S28	0.975	1.000	0.975
S29	1.002	0.982	1.021

Table 3. Average carbon productivity indexes of 29 manufacturing sectors in Shanghai (2001–2016)

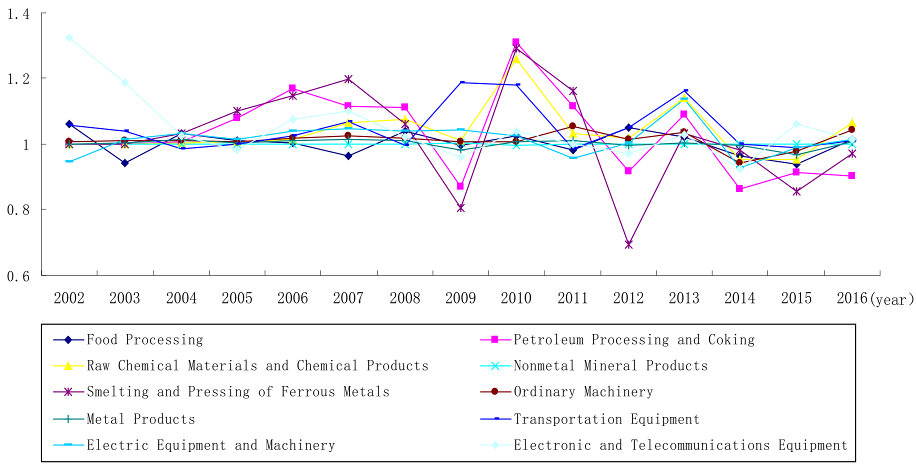

Figure 2. Trends of carbon productivities of ten representative industries: GML index

to 2016. It is evident from Figure 3 that, first, the coefficient of variation in the three samples has great volatility as a whole, hence it is hard to conclude that significant σ convergence exactly exists. Compared to that of the overall industry and polluting sectors, the volatility of the clean sectors is greater. Second, in manufacturing industry, the coefficient of variation is relatively stable over the period 2002–2007 and decrease gradually over the period 2008–2016, whereas it has a short-term sharp rise over the period 2007–2008. Third, during 2002–2016, for the subsectors, the carbon productivity across the clean sectors shows a similar evolution trend as that across the overall manufacturing sectors, which presents σ convergence trend over the two periods 2002–2007 and 2008–2016, whereas the carbon productivity across the polluting sectors during the two periods does not display obvious trend of convergence or divergence.

4.2.2 Absolute β convergence test. Table 4 provides the estimated results of the absolute β convergence of carbon productivity across the manufacturing sectors, as well as the specification test statistics. The fixed effects (FE) model should be chosen based on Hausman test results. As shown in Table 4, β is negative and significant at 1% significance level, meaning the existence of absolute β convergence and sectors with low initial carbon productivities are catching up with the sectors with high initial levels and will eventually reach a common steady state. Similar to σ convergence, after dividing the manufacturing sectors into clean sectors and polluting sectors, the empirical test results show that both subsamples display strong evidence of absolute β convergence. It also shows that the convergence rate is higher in the clean sectors than that in the polluting sectors, whereas the manufacturing sectors as a whole is somewhere in between.

4.2.3 Conditional β convergence test. Table 5 displays the estimated results of conditional β convergence test. In addition to the manufacturing sectors as a whole,

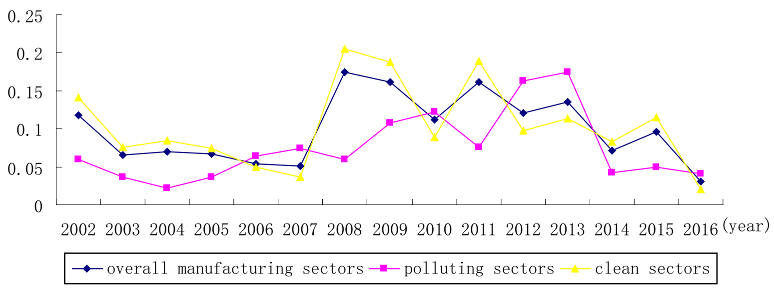

Figure 3. Trends of coefficient of variation for carbon productivity of manufacturing sectors

Coefficients and tests	Manufacturing sectors as a whole	Polluting sectors	Clean sectors
B	−0.1153*** (−7.22)	−0.0524*** (−2.69)	−0.1334*** (−6.37)
C	0.0019***	0.0063	0.0078***
R^2	0.0963	0.0393	0.1128
F or Wald	52.14 [0.0000]	7.26 [0.0070]	40.61 [0.0000]
Hausman test	5.00 [0.0820]	0.01 [0.9957]	6.89 [0.0319]
Model	FE	RE	FE
Number of observation	406	140	266

Notes: Figures in parentheses are z-statistics and figures in brackets represent p values, ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

Table 4. Estimated results of absolute β convergence test

according to the previous classification, Table 5 also presents the test results in the two classification sectors. The serial correlation tests in all regressions reject the absence of the first-order serial correlation (AR1), whereas fails to reject the hypothesis of the absence of second-order serial correlation (AR2), suggesting that serial correlation is not displayed in the error terms. Therefore, the estimator is proved to be consistent. Moreover, the Sargan test does not reject the null hypothesis in all regressions, indicating that the instruments are valid.

As indicated in Table 5 that, first, for the whole manufacturing industry, the estimated coefficient is significantly negative, indicating the presence of conditional β convergence for carbon productivity across the manufacturing sectors in Shanghai, with sectors converging to different steady states. Second, concerning the control variables, the coefficient of firm size is positive and significant at the 1% level, implying that the expansion of firm size contributes to promoting the growth of carbon productivity. In fact, Shanghai's manufacturing industry lacks large-scale firms and the concentration of each sector is low. Therefore, it is vital to further increase investment and expand the firm size to achieve economies of scale. The coefficient of the industry structure is also significantly positive at the 1% level. The reason might be that the effectiveness of structural adjustment policies of Shanghai's manufacturing industry is gradually emerging and the industry's focus is on sectors with high carbon productivities. Actually, for the top five Shanghai's manufacturing sectors in terms of output value in 2016, whose output value accounted for 60.37% of that of the whole manufacturing industry, their carbon productivities are generally greater than the average level of the whole industry. With regard to capital deepening, the carbon productivity decreases as capital deepens. The results are consistent with the findings of Shao *et al.* (2016), where the negative relationship between capital deepening and efficiency incorporating environmental impacts has been verified. The increase in capital deepening means that the manufacturing is transformed from labor-intensive sectors to capital-intensive ones. In China, capital-intensive sectors tend to be heavily polluting ones. Hence, the extensive nature in the process of the heavy industrialization of the manufacturing is an urgent problem to be solved to coordinate the development of environment and manufacturing industry in Shanghai. For the variable of energy consumption structure, the

G	Manufacturing sectors as a whole	Polluting sectors	Clean sectors
$\ln CP_{i,t-1}$	−0.1229*** (−143.86)	−0.0824*** (−13.92)	−0.1305*** (−132.31)
ES	0.0036*** (8.34)	0.0026 (0.69)	0.0036*** (3.00)
IS	0.0078*** (14.00)	−0.0022 (−0.16)	0.0115*** (10.73)
KL	−0.0077*** (−14.99)	−0.0039*** (−2.93)	−0.0120*** (−30.51)
RS	−0.0001*** (−21.21)	−0.0031 (0.1)	−0.0025*** (−8.78)
L1.g	0.4653*** (64.27)	0.3663*** (2.79)	0.4597*** (75.69)
C	0.0598** (17.02)	0.0052 (0.1)	0.0869** (13.69)
Wald	194105.16 [0.0000]	11650.69 [0.0000]	108471.84 [0.0000]
AR(1) test	−2.1263 [0.0335]	−2.0302 [0.0423]	−2.0083 [0.0446]
AR(2) test	−1.2695 [0.2043]	−1.3454 [0.1785]	−1.0093 [0.3128]
Sargan test	23.0675 [0.9961]	5.3894 [1.0000]	13.2689 [1.0000]
Model	SYS-GMM	SYS-GMM	SYS-GMM
Number of observations	377	130	247

Notes: Figures in parentheses are z-statistics and figures in brackets are p values, *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 5. Estimated results of conditional β convergence test

coefficient is also significantly negative, indicating that energy structure has negative impacts on carbon productivity. The current coal-dominated energy consumption structure of China unavoidably lead to more carbon emissions as output grows, thus apparently hindering the carbon productivity growth.

Concerning the estimation results of the subsample, it can be found that, first, similar to the overall manufacturing industry, there is conditional β convergence in the two classification industries. Moreover, the clean sectors have a higher convergence rate than that of the polluting sectors, which is similar to the situations in the absolute β convergence. Second, as with the overall manufacturing industry, the firm size effect and industry structure effect of carbon productivity in the clean sectors are positive and the capital deepening effect and energy consumption structure effect are negative, all being statistically significant at the 1% level. In the polluting sectors, capital deepening has a significantly negative influence, implying that a rise in the capital-labor ratio is not conducive to the growth of carbon productivity in the polluting sectors. The coefficient of firm size is positive whereas the coefficients of the energy consumption structure and industry structure are negative, but none of them is statistically significant.

5. Conclusions and policy implications

In this study, the SBM-DDF and the GML TFP index are used to calculate the carbon productivities of 29 manufacturing subsectors in Shanghai from 2001 to 2016. We find that on the whole, the carbon productivity of Shanghai's manufacturing industry is growing, and technical efficiency instead of technological change makes a main contribution to the growth. Moreover, the annual average negative growth of technological change of some sectors has offset the positive annual growth in technical efficiency. Therefore, there is still much room for improving the carbon productivities of Shanghai's manufacturing sectors by relying on technological progress. It is also found that there is strong heterogeneity in carbon productivity among subsectors.

Furthermore, based on the convergence theories, we empirically investigate the convergence of carbon productivity across the manufacturing sectors in Shanghai. The results show that as a whole, the carbon productivity of Shanghai's manufacturing industry does not exhibit obvious convergence or divergence over time and there is no σ convergence. As far as the subsample is concerned, there is no obvious σ convergence in the polluting sectors but there is σ convergence in the clean sectors as in the overall industry over the periods 2002–2007 and 2008–2016, whereas the carbon productivity in the polluting manufacturing sector shows no obvious convergence or divergence during the two periods. However, the carbon productivity of Shanghai's manufacturing industry shows an absolute β convergence characteristic. The sectors with low carbon productivities grow faster than the sectors with high carbon productivities. There is also an absolute convergence β trend in both classification sectors, and the absolute β convergence rate in the clean sectors is higher than that in the polluting sectors. Using the dynamic panel data system GMM estimator to study the conditional β convergence of manufacturing carbon productivity, we find that these subsectors have different steady states and approach their respective steady-state levels over time. There is conditional β convergence in both subsamples. Besides, the convergence rate is also higher in the clean sectors than in the polluting sectors. Moreover, the impacts of firm size and industry structure on the growth of manufacturing carbon productivity in Shanghai are significantly positive, whereas the impacts of energy consumption structure and capital deepening are negative and statistically significant.

Based on the findings, the following policy recommendations are given to improve the carbon productivity of Shanghai's manufacturing industry.

The first is to promote technological innovation in enterprises and strive to improve the level of technological innovation. Technological changes, such as the progress on energy-saving technology, renewable energy, clean energy and new energy technologies and clean and efficient use of coal technology, are all significant for enterprises within the investigated sectors to implement. However, there are limitations within technological changes of enterprises in Shanghai's manufacturing industry as follows:

- The constraints of technological innovation are mainly reflected in the lack of innovative talents. In terms of finding high-level innovative talents, Shanghai lags behind Beijing and foreign metropolises.
- The negative externality of CO_2 emissions often leads to an insufficient incentive for enterprises to develop and use energy conservation and emission reduction technology.
- At present, key low-carbon technologies in China are by and large still immature and need to be introduced from advanced countries.

Enterprises in Shanghai attached strategic importance to the introduction and innovation of new technologies, but there is still room for improvement in digesting and absorbing them.

Therefore, we identify three policy recommendations as follows:

(1) It is necessary to strengthen investment in education and staff training, as well as to further improve the talent mechanism of the industry.

(2) Several effective stimulating measures for low-carbon technological innovation should be considered, such as financial support and tax exemptions or reduction policy. In particular, Shanghai as a financial center, should focus on its advantages and promote technological innovation by further improving its financial services, e.g., preferential access to credits. It is advisable for the government to provide R&D subsidies and R&D innovation funds to encourage enterprises with low-carbon productivity to engage them in R&D activities on energy-saving and carbon-reduction technologies (Liu *et al.*, 2019).

(3) To start with the establishment of demonstration projects, Shanghai can actively promote cooperation with major international companies and introduce green technologies through cooperation, learning and reproducing those technologies.

Moreover, focusing on the key manufacturing sectors in Shanghai, we recommend that Shanghai take the lead in fully integrating the national initiatives to transform and upgrade the manufacturing industry, e.g. "Made in China 2025" and "Internet Plus." The transformation and upgrading of the manufacturing industry as well as vigorously developing intelligent manufacturing should be taken as the main direction of promoting the international competitiveness of manufacturing industry.

The second is to expand the scale of enterprises and effectively exert economies of scale. Shanghai's manufacturing industry lacks large-scale enterprise groups, especially large innovation-led enterprises. It is necessary to further increase investment and expand the scale of enterprises to achieve scale efficiency. It should reasonably integrate industry resources, rectify "low-small" enterprises and excess backward production capacity, as well as increase the merger and reorganization of manufacturing quality enterprises to form economies of scale. Simultaneously, it makes sense to intensify the cultivation of leading enterprise groups, which play a leading and demonstrative role in Shanghai's manufacturing in terms of innovation capabilities, brand contributions and economic benefits. Moreover, as there is an obvious heterogeneity among subsectors, the sectoral differences should be considered as well when the related policies and measures are formulated.

The third is to optimize the industry structure and promote industrial upgrading. Industrial structure is a large contributor to the carbon productivity growth of Shanghai's manufacturing industry. Therefore, the key to the improvement of the carbon productivity of Shanghai's manufacturing lies in the optimization and adjustment of the industry structure and promoting the transformation from resource consumption growth to innovation-driven growth. On the one hand, some sectors with traditionally high consumption and pollution are facing overcapacity problems and the proportion of high value-added sectors and low carbon sectors is still slow. On the other hand, the restructuring of Shanghai's manufacturing is limited by rising factor costs, constraints of environmental capacities and the lack of technological innovations. Hence, industrial transfer should continue to be promoted in Shanghai's manufacturing industry. At the same time, it is necessary to formulate key technological transformation projects to promote industrial restructuring. Moreover, it is suggested to appropriately promote the development of subsectors with high-carbon productivities, e.g. transportation equipment and telecommunications equipment, which tend to coordinate the sectoral economic growth with carbon emissions reduction, whereas restricting the development of subsectors with low-carbon productivities and low industrial relevance, e.g. nonmetal mineral products.

The fourth is to optimize the energy structure and reduce CO_2 emissions. To improve the carbon productivity, it is necessary to pay attention to how to achieve CO_2 emissions reduction without sacrificing economic benefits. This requires reasonable reduction of the proportion of high-carbon energy consumption such as oil and coal in the actual production process. Limited by the energy resources, Shanghai's energy supply mainly originates from other regions of China. Therefore, relying on comparative technical advantages, Shanghai can seek cooperation with regions with better natural conditions in developing and adopting clean energy sources. Besides, it is advisable to promote clean production and encourage enterprises to apply advanced technologies and equipment for pollution reduction and energy conservation.

Notes

1. The two sectors removed in this paper are "Utilization of Waste" and "Repair Service of Metal Products, Machinery and Equipment."
2. The 29 manufacturing subsectors chosen in this paper are: food processing (S1), food production (S2), beverage production (S3), tobacco processing (S4), textile industry (S5), garments and other fiber products (S6), leather, furs, down and related products (S7), timber processing, bamboo, cane, palm and straw products (S8), furniture manufacturing (S9), papermaking and paper products (S10), printing and record medium reproduction (S11), cultural, educational and sports articles (S12), petroleum processing and coking (S13), raw chemical materials and chemical products (S14), medical and pharmaceutical products (S15), chemical fiber (S16), rubber products (S17), plastic products (S18), nonmetal mineral products (S19), smelting and pressing of ferrous metals (S20), smelting and pressing of nonferrous metals (S21), metal products (S22), ordinary machinery (S23), equipment for special purpose (S24), transportation equipment (S25), electric equipment and machinery (S26), electronic and telecommunications equipment (S27), instruments, meters cultural and office machinery (S28) and other manufacturing industry (S29).
3. Among these 29 manufacturing sectors, polluting sectors include food processing, food production, textile industry, papermaking and paper products, petroleum processing and coking, raw chemical materials and chemical products, chemical fiber, nonmetal mineral products,

smelting and pressing of ferrous metals, and smelting and pressing of nonferrous metals, whereas others belong to clean sectors.

References

Aghayi, N. and Maleki, B. (2016), "Efficiency measurement of DMUs with undesirable outputs under uncertainty based on the directional distance function: application on bank industry", *Energy*, Vol. 112, pp. 376-387.

Ananda, J. and Hampf, B. (2015), "Measuring environmentally sensitive productivity growth: an application to the urban water sector", *Ecological Economics*, Vol. 116, pp. 211-219.

Arabi, B., Munisamy, S. and Emrouznejad, A. (2015), "A new slacks-based measure of Malmquiste-Luenberger index in the presence of undesirable outputs", *Omega*, Vol. 51, pp. 29-37.

Bai, C., Du, K., Yu, Y. and Chen, F. (2019), "Understanding the trend of total factor carbon productivity in the world: insights from convergence analysis", *Energy Economics*, Vol. 81, pp. 698-708.

Chen, C. (2016), "China's industrial green total factor productivity and its determinants: an empirical study based on ML index and dynamic panel data model", *Statistical Research*, Vol. 33 No. 3, pp. 53-62.

Chen, C., Lan, Q., Gao, M. and Sun, Y. (2018), "Green total factor productivity growth and its determinants in China's industrial economy", *Sustainability*, Vol. 10 No. 4, pp. 1-25.

Chung, Y.H., Färe, R. and Grosskopf, S. (1997), "Productivity and undesirable outputs: a directional distance function approach", *Journal of Environmental Management*, Vol. 51 No. 3, pp. 229-240.

Cutlip, L. and Fath, B.D. (2012), "Relationship between carbon emissions and economic development: case study of six countries", *Environment, Development and Sustainability*, Vol. 14 No. 3, pp. 433-453.

Färe, R. and Grosskopf, S. (2010), "Directional distance functions and slacks-based measures of efficiency", *European Journal of Operational Research*, Vol. 200 No. 1, pp. 320-322.

Färe, R., Grosskopf, S. and Pasurka, C.A. (2001), "Accounting for air pollution emissions in measures of state manufacturing productivity growth", *Journal of Regional Science*, Vol. 41 No. 3, pp. 381-409.

Färe, R., Grosskopf, S. and Pasurka, C.A. (2007), "Environmental production functions and environmental directional distance functions", *Energy*, Vol. 32 No. 7, pp. 1055-1066.

Fukuyama, H. and Weber, W.L. (2009), "A directional slacks-based measure of technical inefficiency", *Socio-Economic Planning Sciences*, Vol. 43 No. 4, pp. 274-287.

Hao, Y., Liao, H. and Wei, Y.M. (2015), "Is china's carbon reduction target allocation reasonable? An analysis based on carbon intensity convergence", *Applied Energy*, Vol. 142, pp. 229-239.

Harberger, A. (1978), *Perspectives on Capital and Technology in Less-Developed Countries. ARTIS M J, NOBA Y a R. Contemporary Economic Analysis*, Croom Helm, London, 69-151.

Herrerias, M.J. (2012), "CO_2 weighted convergence across the EU-25 countries (1920-2007",) ", *Applied Energy*, Vol. 92, pp. 9-16.

Huang, B. and Meng, L. (2013), "Convergence of per capita carbon dioxide emissions in urban China: a spatio-temporal perspective", *Applied Geography*, Vol. 40, pp. 21-29.

Kumar, S. and Jain, R.K. (2019), "Carbon-sensitive meta-productivity growth and technological gap: an empirical analysis of Indian thermal power sector", *Energy Economics*, Vol. 81, pp. 104-116.

Liddle, B. (2009), "Electricity intensity convergence in IEA/OECD countries: aggregate and sectoral analysis", *Energy Policy*, Vol. 37 No. 4, pp. 1470-1478.

Liddle, B. (2010), "Revisiting world energy intensity convergence for regional differences", *Applied Energy*, Vol. 87 No. 10, pp. 3218-3225.

Li, Y.D. and Song, L.Y. (2017), "Study on the convergence mechanism of carbon productivity in China: theory and empirical test", *Science of Science and Management of Science and Technology*, Vol. 38 No. 3, pp. 117-125.

Li, W., Wang, W., Wang, Y. and Ali, M. (2018), "Historical growth in total factor carbon productivity of the Chinese industry – a comprehensive analysis", *Journal of Cleaner Production*, Vol. 170, pp. 471-485.

Li, J., Huang, X., Yang, H., Chuai, X. and Wu, C. (2017), "Convergence of carbon intensity in the Yangtze river Delta, China", *Habitat International*, Vol. 60, pp. 58-68.

Liu, J., Yang, Q., Zhang, Y., Zhang, Y., Sun, W. and Xu, Y. (2019), "Analysis of CO_2 emissions in China's manufacturing industry based on extended logarithmic mean division index decomposition", *Sustainability*, Vol. 11 No. 1, pp. 1-28.

Mielnik, O. and Goldemberg, J. (1999), "The evolution of the carbonization index in developing countries", *Energy Policy*, Vol. 27 No. 5, pp. 307-308.

Mulder, P. and De Groot, H.L.F. (2012), "Structural change and convergence of energy intensity across OECD countries, 1970-2005", *Energy Economics*, Vol. 34 No. 6, pp. 1910-1921.

Oh, D.H. (2010), "A global Malmquist–Luenberger productivity index", *Journal of Productivity Analysis*, Vol. 34 No. 3, pp. 183-197.

Pan, X., Pan, X., Li, C., Song, J. and Zhang, J. (2019), "Effects of China's environmental policy on carbon emission efficiency", *International Journal of Climate Change Strategies and Management*, Vol. 11 No. 3, pp. 326-340.

Pastor, J. and Lovell, C. (2007), "Circularity of the Malmquist productivity index", *Economic Theory*, Vol. 33 No. 3, pp. 591-599.

Pastor, J.T., Asmild, M. and Lovell, C.A.K. (2011), "The biennial Malmquist productivity change index", *Socio-Economic Planning Sciences*, Vol. 45 No. 1, pp. 10-15.

Sala-I-Matin, X.X. (1996), "The classical approach to convergence analysis", *The Economic Journal*, Vol. 106 No. 437, pp. 1019-1036.

Shao, S., Luan, R., Yang, Z. and Li, C. (2016), "Does directed technological change get greener: empirical evidence from Shanghai's industrial green development transformation?", *Ecological Indicators*, Vol. 69, pp. 758-770.

Shao, S., Yang, L., Yu, M. and Yu, M. (2011), "Estimation, characteristics, and determinants of energy-related industrial CO_2 emissions in Shanghai (China), 1994–2009", *Energy Policy*, Vol. 39 No. 10, pp. 6476-6494.

Sueyoshi, T., Goto, M. and Wang, D. (2017), "Malmquist index measurement for sustainability enhancement in Chinese municipalities and provinces", *Energy Economics*, Vol. 67, pp. 554-571.

Tao, F., Zhang, H., Hu, J. and Xia, X.H. (2017), "Dynamics of green productivity growth for major Chinese urban agglomerations", *Applied Energy*, Vol. 196, pp. 170-179.

Tone, K. (2001), "A slacks-based measure of efficiency in data envelopment analysis", *European Journal of Operational Research*, Vol. 130 No. 3, pp. 498-509.

Wana, J., Baylis, K. and Mulder, P. (2015), "Trade-facilitated technology spillovers in energy productivity convergence process across EU countries", *Energy Economics*, Vol. 48, pp. 253-264.

Wang, J. and Zhang, K.Z. (2014), "Convergence of carbon dioxide emissions in different sectors in China", *Energy*, Vol. 65, pp. 605-611.

Wang, K., Wei, Y.M. and Zhang, X. (2013), "Energy and emissions efficiency patterns of Chinese regions: a multi-directional efficiency analysis", *Applied Energy*, Vol. 104, pp. 105-116.

Watanabe, M. and Tanaka, K. (2007), "Efficiency analysis of Chinese industry: a directional distance function approach", *Energy Policy*, Vol. 35 No. 12, pp. 6323-6331.

Wu, J., Wu, Y., Guo, X. and Cheong, T.S. (2016), "Convergence of carbon dioxide emissions in Chinese cities: a continuous dynamic distribution approach", *Energy Policy*, Vol. 91, pp. 207-219.

Yang, C. and Wang, T.P. (2016), "Productivity comparison of European airlines: bootstrapping Malmquist indices", *Applied Economics*, Vol. 48 No. 52, pp. 1-11.

Yang, Q., Wan, X.Z. and Ma, H.M. (2015), "Assessing green development efficiency of municipalities and provinces in China integrating models of super-efficiency DEA and Malmquist index", *Sustainability*, Vol. 7 No. 4, pp. 4492-4510.

Yang, J., Zhang, T., Sheng, P. and Shackman, J.D. (2016), "Carbon dioxide emissions and interregional economic convergence in China", *Economic Modelling*, Vol. 52, pp. 672-680.

Zhang, J., Wu, G.Y. and Zhang, J.P. (2004), "The estimation of China's provincial capital stock: 1952-2000", *Economic Research Journal*, No. 10, pp. 35-44.

Zhang, N., Zhou, P. and Kung, C.C. (2015), "Total-factor carbon emission performance of the Chinese transportation industry: a bootstrapped non-radial Malmquist index analysis", *Renewable and Sustainable Energy Reviews*, Vol. 41, pp. 584-593.

Zhao, H. and Lin, B. (2019), "Assessing the energy productivity of China's textile industry under carbon emission constraints", *Journal of Cleaner Production*, Vol. 228, pp. 197-207.

Zhao, X., Burnett, J.W. and Lacombe, D.J. (2015), "Province-level convergence of China's carbon dioxide emissions", *Applied Energy*, Vol. 150, pp. 286-295.

Zhou, P., Ang, B.W. and Han, J.Y. (2010), "Total factor carbon emission performance: a Malmquist index analysis", *Energy Economics*, Vol. 32 No. 1, pp. 194-201.

Further reading

Barro, R. and Sala-I-Martin, X. (1991), "Convergence across states and regions", *Brookings Papers on Economic Activity*, Vol. 1991 No. 1, pp. 107-182.

Arellano, M. and Bond, S. (1991), "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations", *Review of Economic Studies*, Vol. 58 No. 2, pp. 277-297.

Corresponding author

Runong Xu can be contacted at: xurunong@yeah.net