Technological and Economic Development of Economy
ISSN: 2029-4913 / eISSN: 2029-4921
2020 Volume 26 Issue 1: 135–164
https://doi.org/10.3846/tede.2020.11329

MODELLING TECHNOLOGICAL BIAS AND PRODUCTIVITY GROWTH: A CASE STUDY OF CHINA'S THREE URBAN AGGLOMERATIONS

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Received 23 October 2018; accepted 17 August 2019

Abstract. The technological progress in favor of energy conservation and emission reduction will help increase green total factor productivity and thus mitigate China's environmental problems. This study adopts the data envelopment analysis (DEA) to measure the total factor productivity (*TFP*) index of the Chinese three urban agglomerations from 2005 to 2014, and the reasons for its changes are also analyzed. Furthermore, the biases of technological progress from two perspectives of inputs and outputs (including the undersirable output, measured by CO_2 emissions) are estimated. Main results are: (i) During the sample period, the *TFP* of the three urban agglomerations continues to increase, and the main driving force is technological change. (ii) From the perspective of inputs, the Beijing-Tianjin-Hebei prefers to use electricity, whereas the Pearl River Delta and the Yangtze River Delta urban agglomerations tend to use capital and save labor. (iii) From the perspective of outputs, the technological progress of the three major urban agglomerations is significantly biased toward GDP with a slight difference among the three urban agglomerations, which means its technological progress is conducive to reduce CO_2 intensity, symbolizing low carbon development. From this point of view, their economic growth shows a low-carbon trend.

Keywords: total factor productivity, technological progress bias, Malmquist-Luenberger productivity index, data envelopment analysis, urban agglomeration.

JEL Classification: O33.

Introduction

Numerous studies have confirmed that technological progress is the main reason to increase resource utilization efficiency and achieve sustainable growth (Fisher-Vanden, Jefferson, Jingkui, & Jianyi, 2006; Oh, 2009; Yang, Tian, & Ma, 2016). A research report prepared by agencies such as the International Energy Agency, the International Renewable Energy Agency,

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and the United Nations Intergovernmental Panel on Climate Change [IPCC] (2006) also specified that the only feasible means to address climate change in the long run is through technological progress[1]. Technological progress overcomes the risk of energy system technology lock, reduces the dependence of economic growth on high-carbon fossil fuels, and significantly improves the development of clean and zero-carbon energy to form a clean-energy system.

However, technological progress does not improve the utilization efficiency of each input resource evenly, given the elemental bias in technological progress. According to Hicks (1963), technological progress can be neutral, that is, changing the marginal productivity of different elements in the same proportion, or it can be biased, that is, changing the marginal replacement rate between the elements. The latter, technological progress bias, is important for achieving emission reduction and economic growth because the relative usage between energy and other elements can be changed in different proportions. If technological progress is biased to save energy to accomplish low-carbon development, it can provide a greater degree of energy savings relative to other factors of production at a given output. The aforementioned analysis raised the following question: How could the effect of technological progress on the economic development be improved while maintaining a relatively high rate of economic growth, making technological progress favor energy conservation, and reducing environmental pollution for a sound and rapid growth. In this sense, technological progress that is biased towards low-carbon or even zero-carbon is the core and critical path to addressing climate change.

China is one of the biggest victims of climate change. A typical example is the long-term and widespread haze weather in its central and eastern regions in recent years. The Beijing-Tianjin-Hebei, the Yangtze River Delta, and the Pearl River Delta are the three major urban agglomerations with the most abundant resources and the most developed technology and economy in China. However, they are also the regions with the most acute conflicts among resources, environment, and economic development. Taking $PM_{2.5}$ as an example, the *Bulletin on the State of China's Environment* (2016) released by the Ministry of Environmental Protection specifies that the average daily $PM_{2.5}$ concentrations of the Pearl River Delta, the Yangtze River Delta, and the Beijing-Tianjin-Hebei are 32, 46, and 71 (unit $\mu m/m^3$), respectively. These $PM_{2.5}$ concentrations exceed the safety standards (less than 10 $\mu m/m^3$) set by the World Health Organization. As they face increasingly prominent environmental problems, the three major urban agglomerations have become key areas for the Chinese government to control environmental pollution and to realize low-carbon development. The government has announced a series of policies, such as the total amount of regional coal consumption control, regional air pollution control, regional ecological protection compensation mechanism, ecological restoration technology pilot demonstration, and "coal to gas" project to promote the low-carbon development of these major urban agglomerations.

Combined with the aforementioned theoretical analysis and practical problems, in essence, while controlling smog pollution, low-carbon development can also be achieved. All must be achieved by transforming the mode of economic growth, improving the efficiency of

[1] http://paper.people.com.cn/zgnyb/html/2016-04/25/content_1674368.htm

resource allocation and utilization, promoting the substitution of high-carbon fossil fuels by renewable energies, and substantially increasing the catalytic role of technological progress in economic development. The bias of technological progress creates the hope that technological advances will increase the marginal productivity of inputs, such as energy and the environment and the achievement of low-carbon development and environmental pollution control.

Therefore, this study aims to achieve the following: the comprehensive analysis of the status quo of technological progress in the three major urban agglomerations and the bias of technological progress in each urban agglomeration across different periods so as to take the corresponding path of technological progress in promoting low-carbon development, namely it is conducive to energy saving and emission reduction. The specific research strategies are: first, based on data envelopment analysis (DEA) model, we estimate the growth of the total factor productivity (*TFP*) of China's three major urban agglomerations from 2005 to 2014 using the Malmquist-Luenberger productivity index (*MLPI*). Afterward, we decompose the *MLPI* into efficiency and technological change indexes for two parts, namely, to explore and analyze the characteristics and sources of *TFP* changes in the three urban agglomerations. Second, in order to analyze the reasons for the technological change in the three major urban agglomerations, we decomposed technological change index into the three separate indexes: the output biased technological change (*MLOBTECH*), the input biased technological change (*MLIBTECH*), and the magnitude of technological change (*MLMATECH*). Third, this paper derive the technical progress bias comparison tables, and study the input and output biases of various cities and each urban agglomerations across different periods according to the input and output technology progress indexes. Finally, policy implications are proposed.

The contribution of our study is twofold: (i) In the methodology, we combine the DEA model to obtain the technological progress comparison tables of the input and output biases (including the desirable and undesirable outputs) based on the theoretical analysis. In the context of methodology, this combination provides a complete methodological framework using DEA model to study the biases of technological progress (the results of theoretical analysis are provided in Table 1 and Table 2), and it can be used in other areas, such as regional comparison and international comparison. (ii) In the research object, an improved *MLPI* is proposed to measure the *TFP* and technological change indexes of the three urban agglomerations. Furthermore, we decompose the technological change index into the output biased technological change, the input biased technological change, and the magnitude of technological change to analyze the reasons for the technological change in the three major urban agglomerations. We also investigate the technological progress input and output biases in different periods for each region. Due to the importance of the three major urban agglomerations in China's economic growth and the severity of its environmental pollution, this paper takes the three major urban agglomerations as the research object, which has important policy implications for China and other highly polluting countries or regions to control environmental pollution through technological progress.

The subsequent sections of this paper are structured as follows: Section 1 is a brief literature review. Section 2 presents the research method. Section 3 discusses the empirical and results of the analysis. Last Section gives the conclusions and policy suggestions.

1. Literature review

The *TFP* is an important index to measure the contribution rate of technological progress to economic growth. The improvement of *TFP* is key to promoting sustainable growth. Two methods can be generally used to measure *TFP* index: first, parameter method, including Solow residual method, stochastic frontier analysis (SFA) (Cardoso & Ravishankar, 2015; Zhang & Wang, 2015). Second, non-parametric methods, including index method, DEA (Chen & Golley, 2014). Among them, SFA and DEA are two commonly used methods. The SFA method applies only to single-output scenarios (Managi, Opaluch, Jin, & Grigalunas, 2006; Tu & Xiao, 2005), whereas the DEA method does not require any specific function form or distribution assumptions, which suits multi-input and -output situations. Therefore, many papers have used the Malmquist productivity index (*MPI*) method to calculate *TFP* index. Li, Zhang, Gong, and Miao (2015) investigated the *TFP* index of the marine economy of 11 Chinese coastal cities during the period of "11th Five-year Plan" (2006-2010) and comparatively analyzed the regional differences of economic efficiency in these areas. Sueyoshi, Goto, and Wang (2017) used Malmquist index to measure the growth of *TFP* in Chinese municipalities and provinces. The above study considered different input factors and desired output and ignored the undesired output, such as carbon dioxide emissions from production activities.

Given that the *TFP* index measured by *MPI* ignores undesirable pollutant emissions, Chung, Färe, and Grosskopf (1997) included undesirable outputs (pollutant emissions) into the productivity index analysis framework and constructed the *MLPI* based on the proposed directional distance function for measuring the productivity index. The *MLPI* is widely used and becomes the standard analytical tool to measuring the green *TFP*. Li (2013) utilized the DEA method to measure the efficiency of energy-saving and emission reduction in 30 Chinese provinces from 1997 to 2010, the total factor energy efficiency index and its decomposition index (efficiency change and technology change indexes) are measured using the *MLPI* method. The results showed that the increases in energy conservation and emission reduction efficiency are mainly driven by technological progress, whereas the structural adjustment has limited effect. Chen and Golley (2014) used Malmquist-Luenberger to measure the green *TFP* index in the 38 industrial sectors of China from 1980 to 2010. Li and Lin (2015) used the *MLPI* to measure green productivity growth of Chinese industrial sectors during 1998–2011. By using the *MLPI*, Li and Lin (2016) measured the growth rate of Chinese manufacturing green production during the "11th Five-Year" (2006–2010), and found that the price of high Malmquist index is energy consumption and CO_2 emissions. Yu, Shi, Wang, Chang, and Cheng (2016) calculated the efficiency level of the Chinese paper industry with the *MLPI*. Emrouznejad and Yang (2016) measure Chinese manufacturing productivity index considering CO_2 emissions based on the *MLPI*. Du, Chen, and Huang (2017) use the *MLPI* to evaluate the total factor productivity index of China's automobile manufacturing industry from 2005–2012.

For the detailed study of *TFP* change, *MPI* or *MLPI* can be decomposed into technology change and efficiency indexes (Baležentis, 2015; Molinos-Senante, Maziotis, & Sala-Garrido, 2017). Furthermore, Hicks (1963), Harrod (1948), and Solow (1969) respectively define the bias of technological progress according to the causes of technological change following the relative marginal product of each factor of production as follows: Capital-oriented bias, labor-oriented bias, and neutral technical progress. The series of studies conducted by Acemoglu (Acemoglu, 1998, 2002, 2003a, 2003b, 2007; Acemoglu, Carvalho, Ozdaglar, & Tahbaz-Salehi, 2012) redefined the bias of technological progress (e.g., "directed technological change"); by basing on the research paradigm of production function, these studies divided the biased technological progress into two types: "factor bias" and "factor enhancement." The former changes the marginal product radio of input elements, whereas the latter changes the production efficiency of input elements. This method aims to calculate the substitution elasticity among elements.

Many studies have used the production function method to measure the bias of technological progress. The basic steps are: the corresponding production function is derived following the research data, such as the C–D production function (Leimbach, Kriegler, Roming, & Schwanitz, 2017), the revised C–D production function, the CES production function (Klump, McAdam, & Willman, 2007), and the standardized CES production function (Klump, McAdam, & Willman, 2012). Afterward, we took the logarithm of the production function, found the deviation guide, and estimated the substitution elasticity among different elements to assess the factor bias of the technological progress. Given that the CES production function can cover Hicks neutral and non-neutral technical features, it can be converted into C–D production function under certain parameter values. Therefore, empirical studies have mainly utilized the CES production function to estimate non-neutral technical progress and elemental substitution elasticity (Carrara & Marangoni, 2017; Klump et al., 2007; Klump, McAdam, & Willman, 2008). However, the application is limited because theory of CES production function describing economic facts and long-term economic growth is imperfect, and the parameter especially element substitution elasticity of the CES production function is difficult to estimate.

In recent years, scholars have studied the bias of technological progress by combining the DEA model with the *MPI* method (Baležentis, 2014; Chen & Yu, 2014; Li et al., 2018; Mizobuchi, 2015). Barros and Weber (2009) measured airport productivity index based on input-oriented *MPI* and examined the productivity growth and biased technological change in UK airports; furthermore, the productivity index is decomposed to obtain the reasons of the productivity index change and to analyze the input and output biases of technological progress in various airports across different periods. Barros, Guironnet, and Peypoch (2011) found that technological advances favor the use of skilled personnel to study productivity growth and biased technical change in French higher education; only in "learning by doing" can adapt to technological change. Yu and Hsu (2012) used the *MPI* method to measure the changes of Taiwan's airport service productivity and the decomposition of technological change. Li et al. (2018) employed the bias-corrected Malmquist production indices to measure the technical changes in terms of input-saving or input-using in Chinese grain production. Although the above studies have considered different input elements, they only studied the desired output (e.g., as output value, the cargo carrying capacity of an airport, number of passengers, and number of flights). With the increasing prominence of environmental pollution, the economic development must introduce environmental pollution as an undesirable output into the production efficiency evaluation model.

From these previous studies, we can conclude that: i) the majority of studies have used a DEA model to evaluate productivity, however, they cannot test economic assumptions; ii) many studies have investigated the productivity in Chinese provinces or industry sectors, but few have focused on urban agglomerations or even cities; iii) some studies have measured technical change and efficiency change to investigate the reasons for productivity growth, but have failed to identify the types of technological progress, especially when considering the undesirable outputs.

2. Methodology

2.1. Direction distance functions

Zhou and Ang (2008) argued that it was a necessity in studying energy efficiency by considering undesirable outputs such as CO_2 emissions to overcome some modeling bias in empirical analysis. So suppose that K is the decision-making units (*DMUs*), adopt N inputs, $x=\left(x_1,x_2,\ldots,x_N\right)\in R_N^+$ to produce M desirable outputs, $y=\left(y_1,y_2,\ldots,y_M\right)\in R_M^+$, emit I undesirable environmental pollutants, $b=\left(b_1,b_2,\ldots,b_I\right)\in R_I^+$. Therefore, the production possibility set (PPS) is defined as follows:

$$P(x)=\{(y,b): x \text{ can product } (y,b)\}. \quad (1)$$

Instead of technological efficiency, the original Malmquist index used Shephard (1970) output distance functions defined as:

$$D_o(x,y,b)=\inf\{\theta:\frac{(y,b)}{\theta}\in P(x)\}. \quad (2)$$

Given an input vector, the output distance function measures a maximal proportional expansion of the output vector. In this expression, mathematically use the symbol inf{} to indicate "lower bound", that is, the maximum lower bound, it is the abbreviation of the English infimum. θ represents output-oriented technical efficiency and expands the good and bad outputs (y, b) proportionally as much as is feasible. The minimum θ represents the maximal proportional expansion of the output vector. The Malmquist index does not credit reduction of bad outputs, given that the desirable and undesirable outputs are expanded at the same rate. Decision makers often aim to reduce undesirable outputs and increase desired output. The Shephard distance functions cannot describe this feature. Chung et al. (1997) introduced a directional distance function defined as:

$$\vec{D}_o(x,y,b;g)=\sup\{\beta:(y,b)+\beta g\in P(x)\}. \quad (3)$$

In this expression, mathematically use the symbol sup{} to indicate "upper bound", that is, the minimum upper bound, it is the abbreviation of the English supremum. g represents the direction vector where outputs are scaled, in our case, g = (y, −b), i.e. good outputs are increased and bad outputs are decreased. And β denotes the invalid part that needs adjustment. The maximal β represents the maximal proportional expansion of the output vector. Essentially, equation (3) is consistent with equation (2). Equation (2) is defined on the basis of the output distance function, while equation (3) is defined from the directional distance function. The output distance function is a complete characterization of the technology, and it was shown by Färe and Primont (1995) that under weak disposability of outputs, $(y, b) \in P(x) \Leftrightarrow D_0(x, y, b) \leq 1$. Furthermore, Chung et al. (1997) linked the output of the Shephard distance function with the directional distance function (DDF), which seeks to increase the good outputs while simultaneously decreasing the bad outputs. Formally, it is defined as follows:

$$\begin{aligned} \vec{D}_o(x, y, b; y, -b) &= \sup\{\beta : D_o(x, (y, -b) + \beta(y, -b)) \leq 1\} \\ &= \sup\{\beta : (1+\beta) D_o(x, y, -b) \leq 1\} \\ &= \sup\{\beta : \beta \leq \frac{1}{D_o(x, y, -b)} - 1\} \\ &= \frac{1}{D_o(x, y, -b)} - 1 \end{aligned} \tag{4}$$

or equivalently

$$D_o(x, y, -b) = \frac{1}{1 + \vec{D}_o(x, y, b; y, -b)}. \tag{5}$$

The calculation of the distance function can be either input- or output-oriented. Coelli, Rao, O'Donnell, and Battese (2005) proposed that input- and output-oriented distance functions are reciprocal when the scale returns of *DMUs* are constant, that is:

$$D_o(x, y, -b) = \frac{1}{D_i(x, y, -b)}. \tag{6}$$

2.2. Malmquist-Luenberger productivity index

The part of the output growth rate exceeding the factor input growth rate is the *TFP* growth rate (Renuka & Kalirajan, 1999). Similar to Chung et al. (1997), the output-oriented *MLPI* with undesirable output is defined as:

$$MLPI = \sqrt{\frac{(1 + \vec{D}_o^t(x^t, y^t, b^t; y^t, -b^t))(1 + \vec{D}_o^{t+1}(x^t, y^t, b^t; y^t, -b^t))}{(1 + \vec{D}_o^t(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}))(1 + \vec{D}_o^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}))}}. \tag{7}$$

The *TFP* index can be decomposed into the efficiency change index (*MLEFFCH*) and the technology change index (*MLTECH*) two parts. These indexes take the form:

$$MLEFFCH = \frac{(1 + \vec{D}_o^t(x^t, y^t, b^t; y^t, -b^t))}{(1 + \vec{D}_o^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}))}; \tag{8}$$

$$MLTECH = \sqrt{\frac{(1 + \vec{D}_o^{t+1}(x^t, y^t, b^t; y^t, -b^t))(1 + \vec{D}_o^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}))}{(1 + \vec{D}_o^t(x^t, y^t, b^t; y^t, -b^t))(1 + \vec{D}_o^t(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}))}}, \tag{9}$$

where *MLPI* = *MLEFFCH* × *MLTECH*.

The *DMU* moves toward the frontier from period t to $(t + 1)$, $MLPI > 1$ means productivity increased and $MLPI < 1$ means productivity decreased. $MLEFFCH > 1$ means efficiency increased and $MLEFFCH < 1$ means efficiency declined. $MLTECH > 1$ represents technology improved, $MLTECH < 1$ represents technology regressed and $MLTECH = 1$ represents neutral technical progress.

Färe, Grifell-Tatjé, Grosskopf, and Knox Lovell (1997) decomposed *MLTECH* into the output biased technological change (*MLOBTECH*) to further analyze the reasons for the technology change index, the input biased technological change (*MLIBTECH*), and the magnitude of technological change (*MLMATECH*), that is,

$$MLTECH = MLOBTECH \times MLIBTECH \times MLMATECH,$$

where,

$$MLOBTECH = \sqrt{\frac{(1+\vec{D}_o^{t+1}(x^{t+1},y^{t+1},b^{t+1};y^{t+1},-b^{t+1}))}{(1+\vec{D}_o^{t}(x^{t+1},y^{t+1},b^{t+1};y^{t+1},-b^{t+1}))} \times \frac{(1+\vec{D}_o^{t}(x^{t+1},y^{t},b^{t};y^{t},-b^{t}))}{(1+\vec{D}_o^{t+1}(x^{t+1},y^{t},b^{t};y^{t},-b^{t}))}}; \quad (10)$$

$$MLIBTECH = \sqrt{\frac{(1+\vec{D}_o^{t}(x^{t},y^{t},b^{t};y^{t},-b^{t}))}{(1+\vec{D}_o^{t+1}(x^{t},y^{t},b^{t};y^{t},-b^{t}))} \times \frac{(1+\vec{D}_o^{t+1}(x^{t+1},y^{t},b^{t};y^{t},-b^{t}))}{(1+\vec{D}_o^{t}(x^{t+1},y^{t},b^{t};y^{t},-b^{t}))}}; \quad (11)$$

$$MLMATECH = \frac{(1+\vec{D}_o^{t+1}(x^{t},y^{t},b^{t};y^{t},-b^{t}))}{(1+\vec{D}_o^{t}(x^{t},y^{t},b^{t};y^{t},-b^{t}))}. \quad (12)$$

MLOBTECH is the geometric mean of the technical change index when the inputs of the period t and $(t + 1)$ are the same but their outputs are different, indicating the output biased technological change. *MLIBTECH* is the input biased technological change index, which refers to the geometric mean of the technology change index when the inputs are different in the two periods and the outputs are the same. *MLMATECH* is the change of technology scale when inputs and outputs in the two periods are the same, indicating the magnitude of technological change. The above expressions can be solved through the linear programming method.

2.3. Technological progress bias

2.3.1. Bias of inputs

Figure 1 describes the meaning of the input biased technological change index. Point A represents the input portfolio in period t whereas E_1 and E_2 represent two different input portfolios in period $(t + 1)$. The isoquant in period t is represented by $L^t(q)$. We assume three possible isoquants in period $(t + 1)$ by $L^{\mathrm{HN}}(q)$, $L^{t+1,1}(q)$, and $L^{t+1,2}(q)$. If from period t to period $(t + 1)$, then the marginal substitution rate of the two inputs remained constant (i.e., Hicks neutral technical progress) and the isoquant in period $(t + 1)$ is maintained by $L^{\mathrm{HN}}(q)$. If *DMUs* is in favor of technological progress, then two situations will be discussed.

1. $L^{t+1,1}(q)$: The marginal substitution rate at any point on the isoquant is equal to the absolute value of the slope at that point on the isoquant. Comparing $L^{t+1,1}(q)$ and $L^t(q)$,

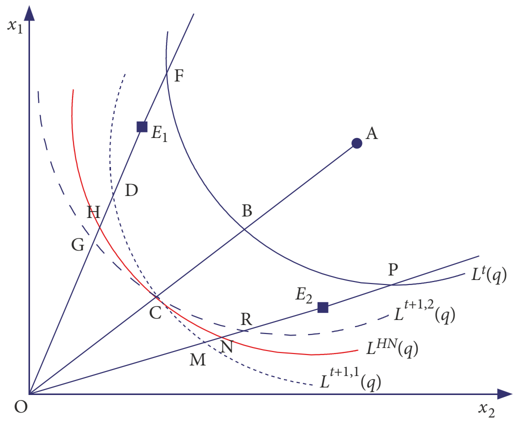

Figure 1. Input biased technological change and input requirement sets

when the input mix is constant, the marginal substitution rate of the input factor x_2 to x_1 in period $(t+1)$ is greater than that in period t. Therefore, from period t to $(t+1)$, the technological progress tends to save x_1, and use x_2 (x_1 – saving, x_2 – using). According to the calculation results of *MLIBTECH* combined with Figure 1, we can obtain the above rules to judge the technological progress bias of inputs, as follows:

Under the condition of constant returns to scale, using Formulas (5) and (6), Formula (11) can be transformed into:

$$MLIBTECH = \sqrt{\frac{\vec{D}_i^t(x^t, y^t, b^t; y^t, -b^t)}{\vec{D}_i^{t+1}(x^t, y^t, b^t; y^t, -b^t)} \times \frac{\vec{D}_i^{t+1}(x^{t+1}, y^t, b^t; y^t, -b^t)}{\vec{D}_i^t(x^{t+1}, y^t, b^t; y^t, -b^t)}}. \quad (13)$$

When the input portfolios in period $(t+1)$ is E_1, the two inputs are satisfied: $\frac{x_1^{t+1}}{x_2^{t+1}} > \frac{x_1^t}{x_2^t}$, the input biased technological change index from period t to period $(t+1)$ is $MLIBTECH = \sqrt{\frac{OA/OB}{OA/OC} \times \frac{OE_1/OD}{OE_1/OF}} = \sqrt{\frac{OC/OB}{OD/OF}}$. Given $OC/OB < OD/OF$, $MLIBTECH = \sqrt{\frac{OC/OB}{OD/OF}} < 1$. When the input portfolios in period $(t+1)$ is E_2, then the two inputs are satisfied: $\frac{x_1^{t+1}}{x_2^{t+1}} < \frac{x_1^t}{x_2^t}$, and the input biased technological change index from period t to period $(t+1)$ is $MLIBTECH = \sqrt{\frac{OA/OB}{OA/OC} \times \frac{OE_2/OM}{OE_2/OP}} = \sqrt{\frac{OC/OB}{OM/OP}}$. Given $OC/OB > OM/OP$, $MLIBTECH = \sqrt{\frac{OC/OB}{OD/OF}} > 1$.

2. $L^{t+1,2}(q)$: Comparing $L^{t+1,2}(q)$ and $L^t(q)$, when the input mix is constant, the marginal substitution rate of the input factor x_2 to x_1 in period $(t+1)$ is smaller than that in period t. Hence, the technological progress from period t to $(t+1)$ tends to save x_2 and use x_1 (x_2 – saving, x_1 – using). According to the calculation results of *MLIBTECH* combined with Figure 1, we can obtain the above rules to judge the technological progress bias of inputs as follows:

When the input portfolios in period $(t + 1)$ is E_1, then the two inputs are satisfied: $\frac{x_1^{t+1}}{x_2^{t+1}} > \frac{x_1^t}{x_2^t}$, and the input biased technological change index from period t to $(t + 1)$ is $MLIBTECH = \sqrt{\frac{OA/OB}{OA/OC} \times \frac{OE_1/OG}{OE_1/OF}} = \sqrt{\frac{OC/OB}{OG/OF}}$. And given $OC/OB > OG/OF$, $MLIBTECH = \sqrt{\frac{OC/OB}{OD/OF}} > 1$. When the input portfolios in period $(t + 1)$ is E_2, then the two inputs are satisfied: $\frac{x_1^{t+1}}{x_2^{t+1}} < \frac{x_1^t}{x_2^t}$, and the input biased technological change index from period t to $(t + 1)$ is $MLIBTECH = \sqrt{\frac{OA/OB}{OA/OC} \times \frac{OE_2/OR}{OE_2/OP}} = \sqrt{\frac{OC/OB}{OR/OP}}$. Given $OC/OB < OR/OP$, $MLIBTECH = \sqrt{\frac{OC/OB}{OR/OF}} < 1$.

In the empirical analysis, the data obtained are generally used to quantitatively analyze the observed objects. Therefore, we can obtain a generalized conclusion by summing the four situations discussed above and the neutral technical progress. Different input changes and input bias technology index can be presented Table 1 to determine the input bias of *DMU*.

Table 1. Changes in the input mix and input biased technological change

Input mix	$MLIBTECH > 1$	$MLIBTECH < 1$	$MLIBTECH = 1$
$\frac{x_j^{t+1}}{x_k^{t+1}} > \frac{x_j^t}{x_k^t}$	x_j – using, x_k – saving	x_j – saving, x_k – using	Neutral
$\frac{x_j^{t+1}}{x_k^{t+1}} < \frac{x_j^t}{x_k^t}$	x_j – saving, x_k – using	x_j – using, x_k – saving	Neutral

2.3.2. Bias in the production of outputs

Figure 2 shows the output biased technological changein the two periods. Point A is the output combination in period t; E_1 and E_2 are two different output combinations in period $(t + 1)$. The output possibility set in period t is given by $P^t(x)$, and we assume that $P^{\mathrm{HN}}(x)$, $P^{t+1,1}(x)$ and $P^{t+1,2}(x)$ represent three output possibility curves.

From period t to $(t + 1)$, technological progress with respect to outputs is Hicks' neutral if the marginal rate of transformation between q_1 and q_2 two outputs is constant, and the output possibility set is represented by $P^{\mathrm{HN}}(x)$. If from period t to $(t + 1)$, then the *DUM* is output technological progress bias that should be divided into two situations:

1. $P^{t+1,1}(x)$: The product's marginal rate of transformation is the absolute value of the slope of the output probability curve. Comparing $P^{t+1,1}(x)$ and $P^t(x)$, and holding the mix of outputs constant, if marginal conversion rate of q_2 to q_1 in period $(t + 1)$ is greater than that in period t, then the technological progress favors producing q_1 (y_1 – producing). Combined with Figure 2 and the result of *MLOBTECH* calculated by function (10), we can obtain the above decision rules of the technological progress bias of output as follows:

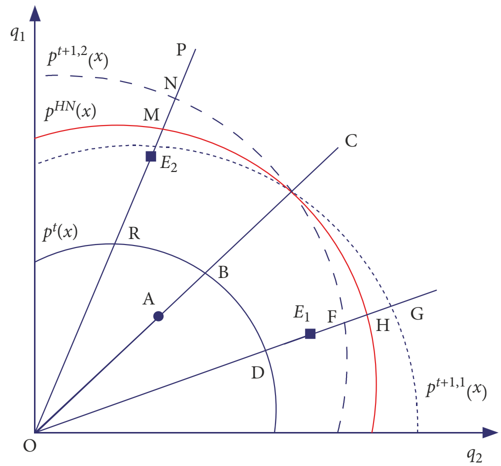

Figure 2. Output biased technological change and production possibility sets [$P(x)$]

When the mix of outputs in period (t + 1) is E_1, the two outputs meet the condition: $\frac{{q_1}^{t+1}}{{q_2}^{t+1}} < \frac{{q_1}^{t}}{{q_2}^{t}}$, and the index of output biased technological changes from period t to (t + 1) is $MLOBTECH = \sqrt{\frac{OA/OC}{OE_1/OF} \times \frac{OE_1/OD}{OA/OB}} = \sqrt{\frac{OB/OC}{OD/OF}}$, given $OB/OC < OD/OF$, $MLOBTECH = \sqrt{\frac{OB/OC}{OD/OF}} < 1$. Correspondingly, when the mix of outputs in period (t + 1) is E_2, then the two outputs meet the condition: $\frac{{q_1}^{t+1}}{{q_2}^{t+1}} > \frac{{q_1}^{t}}{{q_2}^{t}}$, and the index of output biased technological changes from period t to (t + 1) is $MLOBTECH = \sqrt{\frac{OA/OC}{OE_2/OP} \times \frac{OE_2/OR}{OA/OB}} = \sqrt{\frac{OB/OC}{OR/OP}}$, given $OB/OC > OR/OP$, $MLOBTECH = \sqrt{\frac{OB/OC}{OR/OP}} > 1$.

2. $P^{t+1,2}(x)$: Comparing $P^{t+1,2}(x)$ and $P^t(x)$, and holding the mix of outputs constant, the marginal conversion rate of q_2 to q_1 in period (t + 1) is less than that in period t, and the technological progress favors producing q_2 (q_2 – producing). Combined with Figure 2 and the result of *MLOBTECH* calculated by function (10), we can obtain the above decision rules of the technological progress bias of output as follows:

   When the mix of outputs in period (t + 1) is E_1, then the two outputs meet the condition: $\frac{{q_1}^{t+1}}{{q_2}^{t+1}} < \frac{{q_1}^{t}}{{q_2}^{t}}$, and the index of output biased technological changes from period t to (t + 1) is $MLOBTECH = \sqrt{\frac{OA/OC}{OE_1/OG} \times \frac{OE_1/OD}{OA/OB}} = \sqrt{\frac{OB/OC}{OD/OG}}$, given $OB/OC > OD/OG$, $MLOBTECH = \sqrt{\frac{OB/OC}{OD/OG}} > 1$. Correspondingly, when the mix of outputs in period (t + 1) is E_2, then the two outputs meet the condition: $\frac{{q_1}^{t+1}}{{q_2}^{t+1}} > \frac{{q_1}^{t}}{{q_2}^{t}}$, and the index of output biased technological changes from period t to

$(t+1)$ is $MLOBTECH = \sqrt{\frac{OA/OC}{OE_2/OM} \times \frac{OE_2/OR}{OA/OB}} = \sqrt{\frac{OB/OC}{OR/OM}}$, given $OB/OC < OR/OM$, $MLOBTECH = \sqrt{\frac{OB/OC}{OR/OM}} < 1$.

In the empirical analysis, the data are generally used to quantitatively analyze the observed objects. As a result, the conclusion of the four cases discussed above and Hicks' neutral technological regress provide generalized conclusions. Different output changes and output bias technology change index are presented in Table 2.

Table 2. Changes in the output mix and output biased technological change

Output	$MLOBTECH > 1$	$MLOBTECH < 1$	$MLOBTECH = 1$
$\frac{q_m^{t+1}}{q_q^{t+1}} > \frac{q_m^t}{q_q^t}$	q_m – producing	q_q – producing	Neutral
$\frac{q_m^{t+1}}{q_q^{t+1}} < \frac{q_m^t}{q_q^t}$	q_q – producing	q_m – producing	Neutral

3. Results and discussion

3.1. Data

Sample data are gathered from 50 cities in the Pearl River Delta, the Beijing-Tianjin-Hebei, and the Yangtze River Delta urban agglomerations in China from 2005 to 2014, such as the China Statistical Yearbook, China Regional Statistical Yearbook, Yangtze River Delta City Yearbook, Pearl River Delta Urban Group Yearbook, Statistical Yearbook of regions, and Communiques of regions, as well as the CEIC and Cathay Pacific databases. Among them, the variables with price factors are reduced to 2005 constant price series.

The output and input variables used to measure the DEA model are described as follows:

(i) Capital investment: Perpetual inventory method is used to estimate the regional capital stock to replace the capital investment; the unit is 100 million yuan. The initial capital stock is 10 times of the base capital stock (2005). The investment in fixed assets in all prefecture-level cities during the sample period is obtained from the Cathay Pacific database. Given the prefecture-level city's insufficient fixed investment price index, the *CPI* is used to convert the investment in fixed assets into a constant 2005 price. The depreciation rate is estimated by J. Zhang and y. Zhang (2003).

(ii) Labor input: The employment data published by the China Regional Statistical Yearbook and regional statistical yearbook are used directly as labor input, with a unit of 10.000 people.

(iii) Electricity input: A high correlation between electricity consumption and energy consumption exists due to the underestimation of China's energy consumption data to some extent. The electricity consumption data automatically recorded by the electricity meter is accurate. Learning from Lin and Yang (2014), the prefecture-level city electricity consumption data are used to indicate energy consumption, and the unit is kWh.

The data about electricity consumption in the city level comes from the CEIC and Cathay Pacific databases.

(iv) Desirable output (GDP): GDP data comes from the Statistical Yearbook of regions. The nominal GDP will be converted into a constant 2005 price, the unit is 100 million yuan, to maintain consistency with the capital stock.

(v) Undesirable output (CO_2): Carbon dioxide emissions are generally calculated using the carbon emission coefficient from the IPCC (2006). However, the calculation is tough, because obtaining various types of energy consumption data of the prefecture-level cities is difficult. Fortunately, the Chinese government has included the rate of decline in energy intensity (energy consumption per unit of GDP) into the binding indexes of the national economy since 2005, and the prefecture-level cities will publish the energy intensity or energy intensity reduction rate based on 2005, from which the total energy consumption can be calculated. The data about energy intensity and its reduction rate comes from the China Regional Statistical Yearbook, Yangtze River Delta City Yearbook, Pearl River Delta Urban Group Yearbook, and Statistical Yearbook of regions. According to the simple conversion coefficient of standard coal and CO_2 emissions, we can obtain the CO_2 emissions of each prefecture-level city. The comparative analysis shows that the difference between the simple calculation method and the calculation of IPCC is within 5%. Therefore, the present calculation results are relatively reasonable (Jia, 2017), where the unit is 10 thousand tons.

Table 3 describes the statistical description of input and output variables of the three major urban agglomerations in China, wherein the standard deviation of each variable is large.

Table 3. Statistical description of output and input variables in 50 cities during 2005–2014

	Element	Obs	Min	Max	Mean	Std.dev
Input	Capital stock	500	756.1000	40423.1880	7843.0949	8114.9333
	Labor	500	42.0800	1141.0000	354.5634	226.4779
	Electricity	500	5.4993	1410.6100	235.9652	259.5240
Output	GDP	500	110.1800	19690.6000	2694.9652	3143.3279
	CO_2	500	241.6157	27854.5146	5252.1438	5549.7569

3.2. Results and analysis

3.2.1. Productivity growth

In this study, Equations (7)–(12) are used to obtain the change of the *TFP* index and its decomposition indexes. The calculation results show that the annual average *TFP* index (*MLPI*) of the three major urban agglomerations in 2005–2014 is 1.0088, that is, their *TFP* grows at an average annual rate of 0.88%. The decomposition results show that increase in *MLPI* is mainly driven by a technological regression of 2.76%, whereas the efficiency change produced a negative effect of 1.83% on *TFP*. This conclusion is consistent with most findings of studies in China (Oh, 2009; Yang et al., 2016).

Accoring to Table 4, the annual average growth rate of *TFP* in the Yangtze River Delta, the Pearl River Delta, and the Beijing-Tianjin-Hebei urban agglomerations are 0.55%, 1.08%, and 1.48%, respectively. Technological change is the main factor driving the growth of *TFP* in the three major urban agglomerations. Although the technological change in the Yangtze River Delta has an average annual increase of 3.46%, higher than that in the Pearl River Delta and the Beijing-Tianjin-Hebei urban agglomerations, its efficiency change has decreased by 2.81% annually, making the annual average *TFP* growth rate in the Yangtze River Delta the lowest. The above results indicate that the ineffective management or the unreasonable resource allocations of the three major urban agglomerations mainly restrict their *TFP* growth.

Table 4. Annual average *TFP* index and its decomposition of the three urban agglomerations

Urban agglomerations	*MLPI*	*MLEFFCH*	*MLTECH*
Beijing-Tianjin-Hebei	1.0148	0.9966	1.0183
Pearl River Delta	1.0108	0.9896	1.0214
Yangtze River Delta	1.0055	0.9719	1.0346
Overall	1.0088	0.9817	1.0276

Table A1 in the appendix describes the changes in the TFP index and its decomposition components of each city of the three major urban agglomerations. The total factor productivity of thirty-five cities has increased ($MLPI > 1$), it can be judged that the improvement of total factor productivity is mainly due to technological progress ($MLTECH > 1$). Thirty-seven cities haves $MLOBTECH > 1$ meaning technological progress in the production of outputs, while the remaining thirteen cities had $MLOBTECH < 1$ indicating technological regress in the production of the two outputs. For the index of input bias, twelve cities experienced technological regress in the use of inputs ($MLIBTECH < 1$). So, for the magnitude of technological change, Forty-two cities experienced technological progress ($MLMATECH > 1$).

3.2.2. Biased technological progress

3.2.2.1. Input-biased technological progress

Table 5 shows the number of cities that experience a saving/using bias in different input biased technology levels during 2005–2014. The input variables considered are the capital stock (x_1), labor (x_2), and electricity consumption (x_3). We explore three major urban agglomerations' biased technological progress across different periods by comparing the three input variables. The number of cities whose biased various inputs are sorted out in Table 5, and the comparison results between x_1 and x_3, x_2 and x_3, x_1, and x_2 are followed by Figures 3, 5, and 7. We calculated the number of cities of each urban agglomeration biased toward various inputs at different periods to further explore the input bias of the three urban agglomerations, as shown in Figures 4, 6, and 8.

For capital stock (x_1) and electricity consumption (x_3), Figure 3 shows that the input technological progress of most cities in 2006–2007 tend to use capital stock and save electricity, which opposes that in 2007–2010 which tend to use electricity and save capital stock. This situation was again reversed in 2010–2014, which used capital stock and saved electricity.

Table 5. Input biased technological change of the three major urban agglomerations during 2005–2014

Year	Input bias	${x_1}^{t+1}/{x_3}^{t+1} > {x_1}^t/{x_3}^t$	${x_1}^{t+1}/{x_3}^{t+1} < {x_1}^t/{x_3}^t$	${x_2}^{t+1}/{x_3}^{t+1} > {x_2}^t/{x_3}^t$	${x_2}^{t+1}/{x_3}^{t+1} < {x_2}^t/{x_3}^t$	${x_1}^{t+1}/{x_2}^{t+1} > {x_1}^t/{x_2}^t$	${x_1}^{t+1}/{x_2}^{t+1} < {x_1}^t/{x_2}^t$
2005–2006	*MLIBTECH* > 1	0(x_1 – using)	32(x_1 – saving)	1(x_2 – using)	31(x_2 – saving)	16(x_1 – using)	16(x_1 – saving)
	MLIBTECH < 1	1(x_1 – saving)	16(x_1 – using)	0(x_2 – saving)	17(x_2 – using)	9(x_1 – saving)	8(x_1 – using)
	Neutral	1		1		1	
2006–2007	*MLIBTECH* > 1	1(x_1 – using)	20(x_1 – saving)	3(x_2 – using)	18(x_2 – saving)	10(x_1 – using)	11(x_1 – saving)
	MLIBTECH < 1	1(x_1 – saving)	27(x_1 – using)	2(x_2 – saving)	26(x_2 – using)	21(x_1 – saving)	7(x_1 – using)
	Neutral	1		1		1	
2007–2008	*MLIBTECH* > 1	4(x_1 – using)	15(x_1 – saving)	10(x_2 – using)	9(x_2 – saving)	7(x_1 – using)	12(x_1 – saving)
	MLIBTECH < 1	13(x_1 – saving)	16(x_1 – using)	8(x_2 – saving)	21(x_2 – using)	26(x_1 – saving)	3(x_1 – using)
	Neutral	2		2		2	
2008–2009	*MLIBTECH* > 1	13(x_1 – using)	11(x_1 – saving)	4(x_2 – using)	20(x_2 – saving)	21(x_1 – using)	3(x_1 – saving)
	MLIBTECH < 1	14(x_1 – saving)	10(x_1 – using)	4(x_2 – saving)	20(x_2 – using)	22(x_1 – saving)	2(x_1 – using)
	Neutral	2		2		2	
2009–2010	*MLIBTECH* > 1	5(x_1 – using)	24(x_1 – saving)	2(x_2 – using)	27(x_2 – saving)	24(x_1 – using)	5(x_1 – saving)
	MLIBTECH < 1	5(x_1 – saving)	15(x_1 – using)	1(x_2 – saving)	19(x_2 – using)	19(x_1 – saving)	1(x_1 – using)
	Neutral	1		1		1	
2010–2011	*MLIBTECH* > 1	10(x_1 – using)	8(x_1 – saving)	4(x_2 – using)	14(x_2 – saving)	16(x_1 – using)	2(x_1 – saving)
	MLIBTECH < 1	10(x_1 – saving)	21(x_1 – using)	3(x_2 – saving)	28(x_2 – using)	28(x_1 – saving)	3(x_1 – using)
	Neutral	1		1		1	
2011–2012	*MLIBTECH* > 1	27(x_1 – using)	4(x_1 – saving)	7(x_2 – using)	24(x_2 – saving)	29(x_1 – using)	2(x_1 – saving)
	MLIBTECH < 1	14(x_1 – saving)	4(x_1 – using)	1(x_2 – saving)	17(x_2 – using)	17(x_1 – saving)	1(x_1 – using)
	Neutral	1		1		1	
2012–2013	*MLIBTECH* > 1	14(x_1 – using)	4(x_1 – saving)	0(x_2 – using)	19(x_2 – saving)	14(x_1 – using)	4(x_1 – saving)
	MLIBTECH < 1	19(x_1 – saving)	12(x_1 – using)	5(x_2 – saving)	25(x_2 – using)	19(x_1 – saving)	12(x_1 – using)
	Neutral	1		1		1	
2013–2014	*MLIBTECH* > 1	29(x_1 – using)	10(x_1 – saving)	6(x_2 – using)	31(x_2 – saving)	38(x_1 – using)	1(x_1 – saving)
	MLIBTECH < 1	9(x_1 – saving)	2(x_1 – using)	9(x_2 – saving)	4(x_2 – using)	6(x_1 – saving)	5(x_1 – using)
	Neutral	0		0		0	

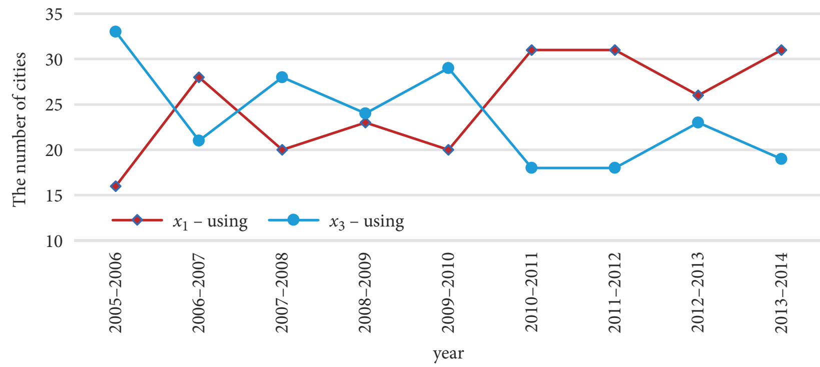

Figure 3. Input biased technological changes of capital stock (x_1) and electricity consumption (x_3)

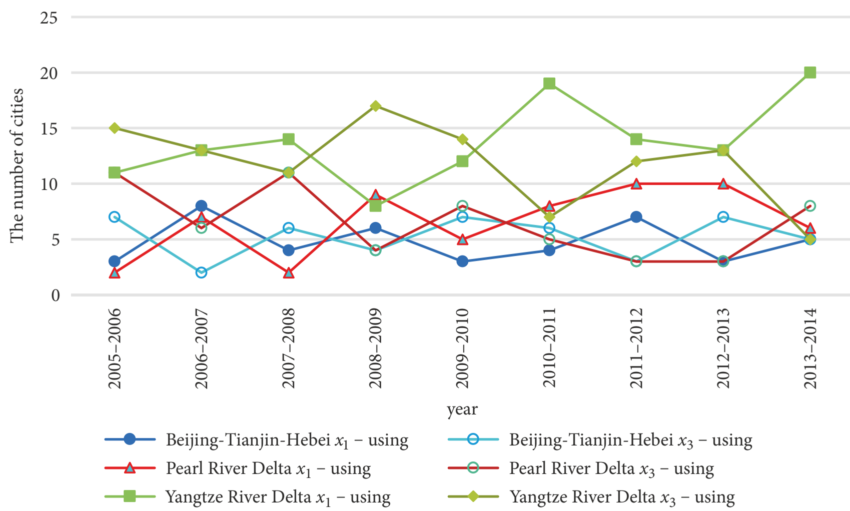

Figure 4. Input biased technological changes of capital stock (x_1) and electricity consumption (x_3) in each of the urban agglomerations

Specifically, in recent years, most cities in the three major urban agglomerations have tended to use more capital stock and to reduce electricity investment. This may be because in response to the 2008 financial crisis, on November 5, 2009, the Chinese government released a "4 trillion-yuan two-year investment plan", which led to sizable investment projects launched to promote capital use.

The comparison of Figures 4 and 3 shows that the input technological change in Yangtze River Delta only in 2007–2008 is dissimilar to that in the overall three urban agglomerations. During this period, the input technological progress in the Yangtze River Delta tended to use capital stock and save electricity. The Pearl River Delta in 2008–2009 and 2013–2014 is different from the overall situation of the three urban agglomerations. The input technological progress in the Pearl River Delta tended to use capital stock and save electricity in 2008–2009, but in 2013–2014, it tended to use electricity and save capital stock. The input technological change in Beijing-Tianjin-Hebei is dissimilar to that in the overall three urban agglomerations in 2008–2009, 2010–2011, and 2012–2013, it tended to use capital stock and save electricity in 2008–2009, to use electricity and save capital stock in 2010–2011, and to use electricity and save capital stock in 2012–2013. Compared with the overall three major urban agglomerations, the Beijing-Tianjin-Hebei prefers using electricity to drive economic growth during the crucial period of response to the 2008 financial crisis. This is closely related to the development of heavy industry in the Beijing-Tianjin-Hebei region, which brought serious environmental pollution problems to the region.

For the labor (x_2) and electricity consumption (x_3) of the three major urban agglomerations overall, Figure 5 shows that the use bias of labor and electricity consumption is unstable. The input technological progress of most cities in the three major unban agglomerations are biased to use electricity (x_3) and save labor (x_2) in 2005–2006, 2009–2010, and 2013–2014. The input biased technological progresses of labor and electricity consumption in these 50 cities are unnoticeable in 2008–2009, 2011–2012 and 2012–2013, whereas it favored to use labor and save electricity in the other periods.

Compared with Figures 6 and 5, we can find that the input technological change in the Yangtze River Delta is similar with that of the three urban agglomerations overall and dissimilar only in 2008–2010 and 2011–2013. The input technological progress of the Yangtze River Delta tended to use electricity and save labor in 2008–2009 and tended to use labor and save electricity in 2009–2010 and 2011–2013. The Pearl River Delta in most years is different from the overall situation. The Yangtze River Delta experienced an electricity-using and labor-saving bias in 2005–2006, and a labor-using and electricity-saving bias in 2006–2007 and 2007–2008. The input technological progress of the Pearl River Delta always tended to use electricity and save labor after 2008. The input bias in Beijing-Tianjin-Hebei during the whole sample period differed in each period and without an evident bias tendency. Overall, the input technological progress tended to use labor and save electricity in the Yangtze River Delta and to use electricity and save labor in the Pearl River Delta through the whole sample period, which is not obvious in the Beijing-Tianjin-Hebei.

For capital stock (x_1) and labor (x_2), Figure 7 shows that the input technological progress of most cities in 2005–2011 tended to use labor and save capital stock and that the input technological progress of most cities in the three major urban agglomerations experienced an unnoticeable bias in 2005–2006, 2008–2009 and 2009–2010. The input technological progress in most cities in the three major urban agglomerations tended to use capital stock and save labor in 2011–2012 and 2013–2014 and tended to use labor and save capital stock in 2012–2013. The three major urban agglomerations' input technological progress is mainly devoted to labor using and capital stock saving before 2011. However, the tendency of capital stock using and labor saving occurred tentatively after 2011. Over 85% of the three major urban agglomerations' cities are biased toward capital stock using and labor saving in 2013–2014. This finding can be attributed to the "shortage of migrant workers" in the eastern coastal areas in recent years.

Combined with the information in Figure 8, we further analyzed whether or not the input technological progress of each urban agglomeration at different periods is biased toward the use of capital stock or labor. The input technological progress in the Yangtze River Delta favored the labor using and saving capital stock in 2005–2013, and cheap labor helped boost the manufacturing industry in the Yangtze River Delta; however, a clear bias is observed to-

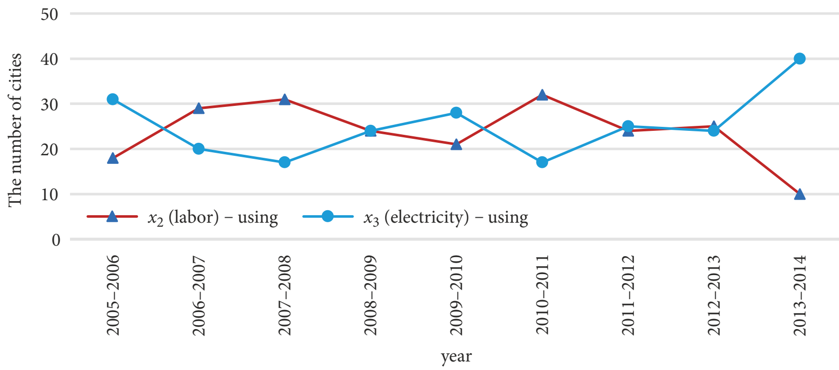

Figure 5. Input biased technological changes of labor (x_2) and electricity consumption (x_3)

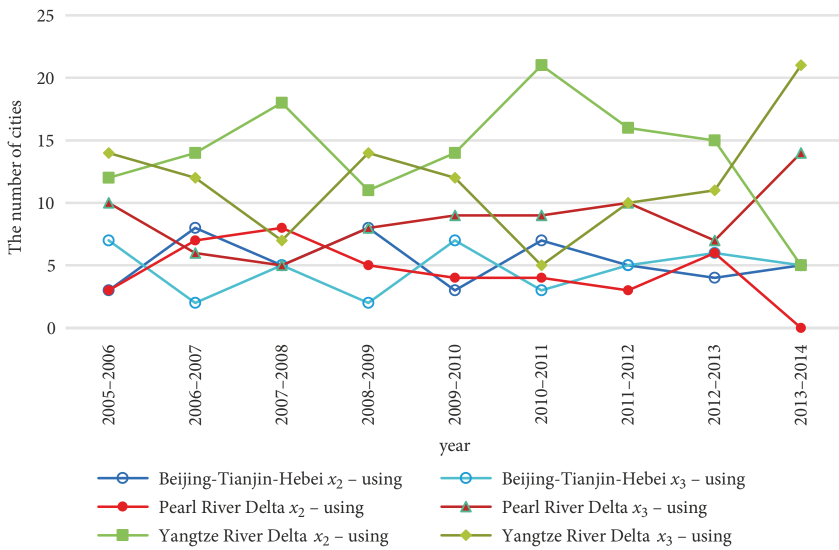

Figure 6. Input biased technological changes of labor (x_2) and electricity consumption (x_3) in each of the urban agglomerations

ward capital stock using and labor saving in 2013–2014. The input technological progress of Pearl River Delta in 2005–2008 tended to use labor and capital stock saving and tended to use capital stock and save labor from 2008 to 2014. The labor advantage of manufacturing in the Pearl River Delta disappeared. The input technological progress change in Beijing-Tianjin-Hebei changed in different periods, and it experienced a capital stock using and labor-saving bias in 2005–2006 and a labor using and capital stock saving bias in 2006–2009. Affected by the economic stimulus policies in 2009, the input technological progress in 2009–2010 tended to use capital stock and save labor, and the input bias in each period differed afterward. By contrasting the biases of the three urban agglomerations at different periods, we found that "shortage of migrant workers" impacts the Pearl River Delta; thus, it passively used more capital to develop its manufacturing industry, followed by the Yangtze River Delta. The "shortage of migrant workers" has no evident influence on Beijing-Tianjin-Hebei.

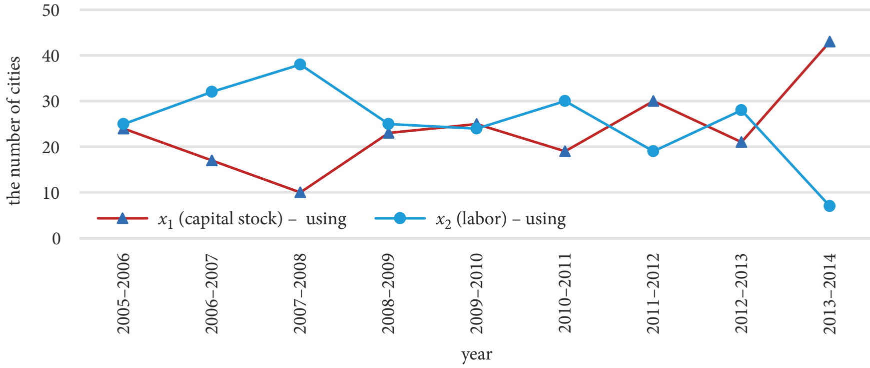

Figure 7. Input biased technological changes of capital stock (x_1) and labor (x_2)

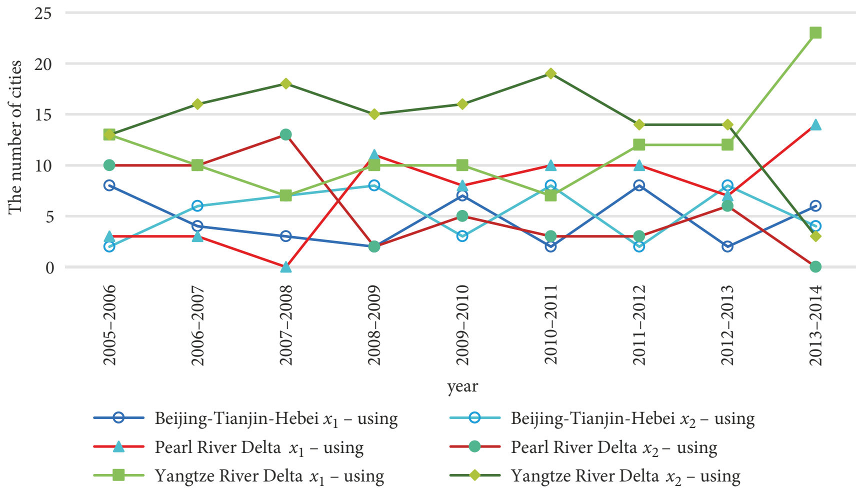

Figure 8. Input biased technological changes of capital stock (x_1) and labor (x_2) in each of the urban agglomerations

Based on the analyses in Figures 3, 5, and 7, we can obtain the order of the technological progress factors bias of the three major urban agglomerations in China, as shown in Figure 9. During the whole sample period, the input technological progress bias varied. No obvious bias in input technological progress is observed in 2008–2009. Since 2010, the input elements have basically tended to use capital stock, labor using, and electricity saving. By comprehensively analyzing Figures 4, 6, and 8, we can roughly evaluate the biased order of each urban agglomeration for input technological progress, as shown in Table 6. For the Pearl River Delta, the input technological progress tended to use electricity and save capital stock since 2010, to use capital stock and save labor in 2008–2014. The labor advantage of manufacturing in the Pearl River Delta disappeared. For the Beijing-Tianjin-Hebei, the "shortage of migrant workers" has no evident influence on Beijing-Tianjin-Hebei. For the Yangtze River Delta, the input technological progress tended to use labor and save electricity through the whole sample period. The input technological progress favored the labor using and saving capital stock in 2005–2013, and cheap labor helped boost the manufacturing industry in the Yangtze River Delta.

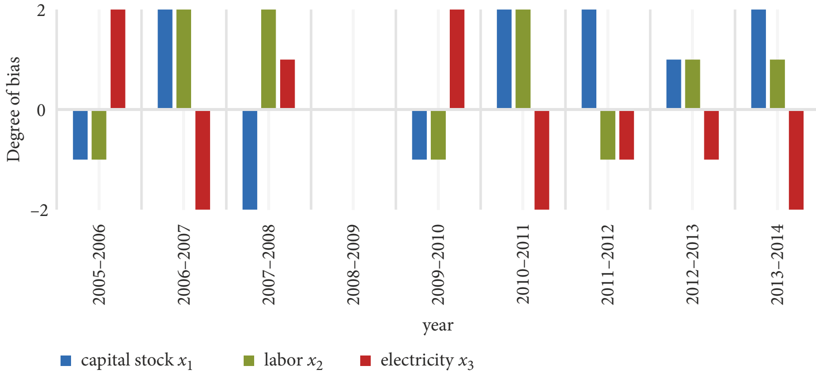

Figure 9. Order of input technological progress factors bias of the three major urban agglomerations[2]

Table 6. Order of input technological progress bias of each urban agglomeration

Urban agglomeration	Biased order
Pearl River Delta	Electricity (x_3) > Capital stock (x_1) > Labor (x_2)
Beijing-Tianjin-Hebei	Electricity (x_3) > Labor (x_2) > Capital stock (x_1)
Yangtze River Delta	Labor (x_2) > Capital stock (x_1) > Electricity (x_3)

3.2.2.2. Output-biased technological progress

Table 7 shows the number of cities that experienced a saving/using bias in different output biased technology level during 2005–2014. The output variables considered are the desirable output GDP (y_1) and undesirable output CO_2 (y_2). In the economic development process, the output GDP is often accompanied by the impact on the natural environment. In this paper, CO_2 emissions are incorporated into the *MLPI* as undesirable output to internalize the negative externality of the undesirable output.

The data in Table 7 is slightly collated to obtain Figure 10. From 2005 to 2013, the output technological progress is biased toward the output of GDP. This finding means that in most cities of the three major urban agglomerations, the economy focuses in green development in this period. In line with the major pollutants control as a means, the total emission control of major pollutants in 2006–2010 is proposed to promote the upgrade and optimization of industrial structure and to achieve the goal of increasing production without increasing or reducing pollution, which is necessary for environmental constraints. However, the output technological progress of most cities in the three urban agglomerations tended to produce more CO_2 in 2013–2014. This condition is not the expected green economy growth in the context of energy saving and emission reduction. Comparing 2012–2013 and 2013–2014, the changes in the number of cities whose output technological progress bias toward producing GDP or CO_2 is large. This finding may be due to two reasons: firstly, the third national eco-

[2] A correspondence value of more than 0 means that the technological progress is biased to the input, whereas one that is less than 0 means deviating from the input; the absolute value of the order indicates the degree of bias.

Table 7. Output biased technological changes of the three major urban agglomerations during 2005–2014

Year	Output bias	$\left(\frac{y_1}{y_2}\right)^{t+1} > \left(\frac{y_1}{y_2}\right)^{t}$	$\left(\frac{y_1}{y_2}\right)^{t+1} < \left(\frac{y_1}{y_2}\right)^{t}$
2005–2006	*MLOBTECH* < 1	27(y_1 – producing)	2(y_2 – producing)
	MLOBTECH > 1	13(y_2 – producing)	2(y_1 – producing)
	Neutral	6	
2006–2007	*MLOBTECH* < 1	28(y_1 – producing)	3(y_2 – producing)
	MLOBTECH > 1	13(y_2 – producing)	1(y_1 – producing)
	Neutral	5	
2007–2008	*MLOBTECH* < 1	22(y_1 – producing)	3(y_2 – producing)
	MLOBTECH >1	17(y_2 – producing)	0(y_1 – producing)
	Neutral	8	
2008–2009	*MLOBTECH* < 1	23(y_1 – producing)	4(y_2 – producing)
	MLOBTECH > 1	13(y_2 – producing)	0(y_1 – producing)
	Neutral	10	
2009–2010	*MLOBTECH* < 1	21(y_1 – producing)	3 (y_2 – producing)
	MLOBTECH > 1	12(y_2 – producing)	11(y_1 – producing)
	Neutral	3	
2010–2011	*MLOBTECH* < 1	25(y_1 – producing)	8(y_2 – producing)
	MLOBTECH > 1	11(y_2 – producing)	2(y_1 – producing)
	Neutral	4	
2011–2012	*MLOBTECH* < 1	35(y_1 – producing)	0(y_2 – producing)
	MLOBTECH > 1	5(y_2 – producing)	2(y_1 – producing)
	Neutral	8	
2012–2013	*MLOBTECH* < 1	31(y_1 – producing)	3(y_2 – producing)
	MLOBTECH > 1	5(y_2 – producing)	2(y_1 – producing)
	Neutral	9	
2013–2014	*MLOBTECH* < 1	7(y_1 – producing)	2(y_2 – producing)
	MLOBTECH > 1	30(y_2 – producing)	2(y_1 – producing)
	Neutral	9	

nomic census conducted by the State Council of China in 2013 result in a large gap between 2014 and 2013 data, which in turn led to a major change in the output bias in 2013–2014; secondly, unlike Guan et al. (2018), which use national energy-related industrial carbon dioxide emissions data, we used carbon dioxide emissions data from 50 prefecture-level cities of three major urban agglomerations, the data of prefecture-level cities may have poor statistical quality.

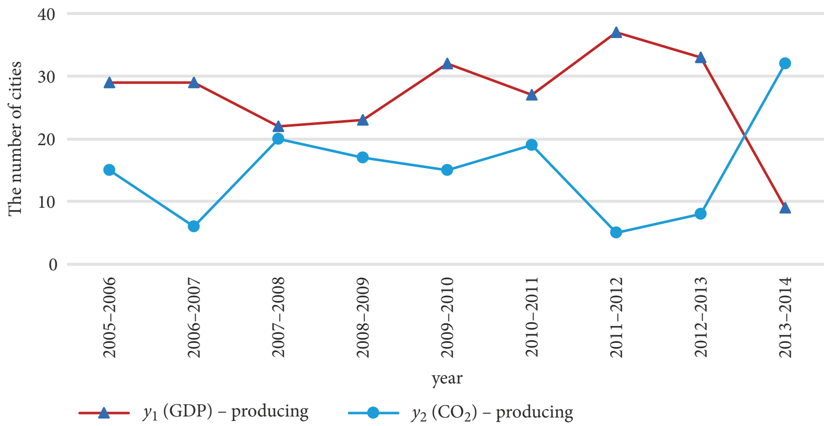

Figure 10. Output biased technological changes of GDP (y_1) and CO_2 (y_2)

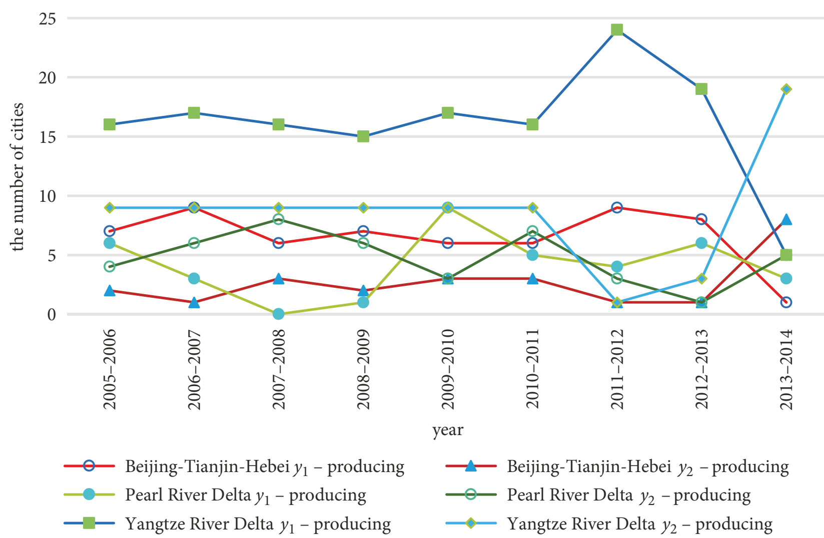

Figure 11. Output biased technological changes of GDP (y_1) and CO_2 (y_2) in each of the urban agglomerations

Figure 11 shows the output biased technological progress of each urban agglomeration in different periods. Comparing Figures 10 and 11, we can find that the output biases of Yangtze River Delta and Beijing-Tianjin-Hebei are similar as that in the overall three major urban agglomerations, the output technological progress is biased toward the output GDP in 2005–2013, the economic development is green. However, output technological progress tended to produce CO_2 in 2013–2014, probably for the reasons stated above. The Pearl River Delta is different from the overall situation, the output technological progress is biased toward GDP in 2005–2006 and 2009–2010 and toward CO_2 in 2006–2009. The economic development in the Pearl River Delta during 2006–2009 is not green, which is inconsistent with the energy saving and emission reduction requirements suggested in the "11th Five-Year Plan." The out-

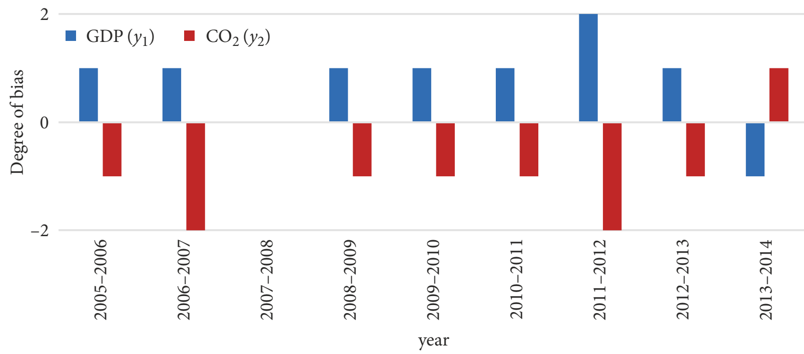

Figure 12. Order of output technological progress factors bias of the three major urban agglomerations

Table 8. Order of output technological progress bias of each of the urban agglomeration

Urban agglomeration	Biased order
Pearl River Delta	/
Beijing-Tianjin-Hebei	GDP (y_1) > CO_2 (y_2)
Yangtze River Delta	GDP (y_1) > CO_2 (y_2)

put biases are not obvious in the two periods 2010–2011 and 2011–2012. Although slightly biased toward CO_2 during 2013–2014, the output technological progress is biased toward the output of GDP during 2012–2013. From the perspective of the whole sample period, the economy of the Pearl River Delta has gradually shifted to green development since 2009.

From the above analysis, we can obtain the order of the technological progress factor bias of the three major urban agglomerations, as shown in Figure 12 and Table 8. During the whole sample period, the three major urban agglomerations' output technological progress is biased toward GDP, in addition to CO_2 in 2013–2014. This means to achieve economic development while reducing CO_2 emissions, thus reducing the CO_2 emission intensity, symbolizing the low-carbon development. That is, their economic development is green. For the three urban agglomerations, the output technological progress in Beijing-Tianjin-Hebei and the Yangtze River Delta tended to yield GDP, whereas that in the Pearl River Delta is not obvious during the sample period.

Conclusions and policy implications

It has become a consensus of the international community to control environmental pollution and achieve sustainable development through technological progress. Taking the Malmquist-Luenberger productivity index to represent the low carbon development level, this paper explores the impact of technological progress bias on low carbon development from both theoretical and empirical levels. Specifically, the *MLPI* of the three major urban agglomerations in China from 2007 to 2014 is calculated based on the DEA. The *TFP* changes are also analyzed. Afterward, the *TFP* index is decomposed into two parts: technology change indexes (*MLTECH*) and the efficiency (*MLEFFCH*), and we analyzed the part that caused the change in *TFP* index in the three urban agglomerations. In addition, we compared the differences among the three urban agglomerations. Furthermore, technological change index is divided into the three separate indexes, namely, the magnitude of technological change (*MLMATECH*), the input biased technological change (*MLIBTECH*), and the output biased technological change (*MLOBTECH*), to analyze the reasons for the three major urban agglomerations' technological change in China. By using the sizes of the input and output bias indexes (greater than 1 or less than 1), we combined the input and output biases (Tables 1 and 2) to obtain the input and output technological progress biases of the three urban agglomerations in different periods. In theory, the factor input bias and output bias results presented in Tables 1 and 2 provided a guidance and analysis framework for similar studies in other regions. In practice, the analytical conclusions of this paper can help reveal the technological progress path to achieve low-carbon growth, and have important implications for other regions. This paper's main conclusions and policy implications are as follows.

First, in the sample period, the average *TFP* of the three major urban agglomerations in neighboring times is constantly increasing, with technological progress as the main factor to improve the average *TFP*. For each urban agglomeration, the technological progress level of the Yangtze River Delta is the highest, followed by the Pearl River Delta, and the Beijing-Tianjin-Hebei is the weakest. Although the technological level of the three urban agglomerations is relatively high, more than 80% of cities have inefficiency problem. This result may be caused by inadequate management and irrational allocation of resources. Although pursuing technological innovation, the three major urban agglomerations in China must focus on strengthening their management and optimizing resource allocation to achieve rapid and sound economic development.

Second, for the input variables capital stock and electricity consumption, the input technological progress of the overall three major urban agglomerations in recent years tended to favor capital stock using and electricity saving given the economic stimulus policies in 2009. For each urban agglomeration, the input technological progress of the Yangtze River Delta and the Pearl River Delta is biased toward the capital stock use and electricity saving in recent years. Moreover, the input technological progress opposes that in the Beijing-Tianjin-Hebei because of the heavy industrial development. The reliance of the Beijing-Tianjin-Hebei region on electricity to promote economic development has brought serious environmental pollution, and this region should strengthen its management to improve energy efficiency, reduce its energy dependence, actively develop new energy sources, and use clean energy to reduce pollution levels.

Third, for labor and electricity consumption, the three major urban agglomerations' input biased technological progress is slightly different in each period without obvious input bias. For each urban agglomeration, the input technological progress in the Pearl River Delta has been devoted to electricity using and labor saving since 2008 due to the phenomenon of "shortage of migrant workers" in the coastal areas of eastern China in recent years. The technological progress in the Yangtze River Delta has been mainly biased toward electricity using and labor saving since 2009. However, the input bias of Beijing-Tianjin-Hebei from

2009 is not obvious. "Shortage of migrant workers" has the largest impact on the Pearl River Delta at the earliest, followed by the Yangtze River Delta, and it has no obvious impact on the Beijing-Tianjin-Hebei region.

Fourth, for capital stock and labor, the three major urban agglomerations' input technological progress is biased toward labor using and capital stock saving in 2005–2011, which began to go in reverse recently. For each urban agglomeration, the Pearl River Delta's technological progress in 2008–2014 is biased toward capital stock using and labor saving, and its labor advantages for the manufacturing industry disappeared. The input technological progress of the Yangtze River Delta in 2005–2013 is bias toward labor using and capital stock saving, and cheap labor contributed to the growth of the manufacturing industry. However, a clear bias toward capital stock using and labor saving is observed in 2013–2014. The input bias in Beijing-Tianjin-Hebei devoted no evident trend changes. Contrasting the two input variables of capital and labor, the effect of "labor shortage" on technological progress also exists. The Yangtze River Delta and the Pearl River Delta urban agglomerations should be further established to improve the guarantee system for migrant workers and enhance the living and working conditions of migrant workers that will attract some migrant workers back to coastal areas. Simultaneously, we must further increase the support for small and medium-sized enterprises in terms of credit and tax revenue to enhance their survival and developmental abilities.

Finally, for the output various GDP and CO_2, the three major urban agglomerations' output technological progress is biased toward the output of GDP, and the economic development is green. For each urban agglomeration, the Beijing-Tianjin-Hebei and the Yangtze River Delta are in line with the overall output bias, whereas before 2009, the output technological progress of the Pearl River Delta is biased toward the output of CO_2. Afterward, the Pearl River Delta economy gradually turned to green development. In pursuit of rapid economic development, the Pearl River Delta should strengthen its business management and actively improve the welfare system for its employees.

Acknowledgements

We acknowledge the financial support from the National Natural Science Foundation of China (Nos. 71773028, 71603079, 71804044 and 71974054), the Hunan Natural Science Foundation (No. 2019JJ40039), the International Clean Energy Talent Programme (No. LIUJINFA[2017]5047-201702660011), Beijing Finance Project (No. PXM2019-178216-000004-00341472-FCG-Innovative project-preresearch).

Author contribution

Ke LI and Hongshan AI designed this study and participated in all phases; Jianying QU and Pan WEI were respnsible for the development of the data analysis. Pinrong JIA was respnsible for data interpretation. Jianying QU and Pan WEI wrote the first draft of the article. Jianying QU wrote the revised manuscript. All authors read and approved the final manuscript.

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APPENDIX

Table A1. Total Factor Productivity Index and its decomposition of each city

Urban agglomerations	City	*MLPI*	*MLEFFCH*	*MLTECH*	*MLMATECH*	*MLOBTECH*	*MLIBTECH*
Beijing-Tianjing-Hebei	Beijing	1.0202	0.9598	1.0630	1.0621	0.9996	1.0013
	Tianjin	1.0263	0.9786	1.0488	1.0461	1.0008	1.0018
	Shijiazhuang	1.0141	0.9824	1.0322	1.0112	1.0047	1.0161
	Tangshan	1.0295	0.9917	1.0381	1.0355	1.0007	1.0019
	Qinghuangdao	1.0236	0.9919	1.0320	1.0271	1.0028	1.0020
	Baoding	1.0032	1.0365	0.9678	0.9983	0.9990	0.9705
	Zhangjiakou	1.0299	0.9994	1.0306	1.0329	1.0003	0.9975
	Chengde	1.0281	1.0283	0.9998	1.0047	1.0031	0.9920
	Cangzhou	0.9923	1.0102	0.9823	0.9775	1.0027	1.0022
	Langfang	0.9823	0.9895	0.9928	0.9608	1.0087	1.0243
Pearl River Delta	Guangzhou	1.0050	0.9703	1.0358	1.0347	1.0003	1.0008
	Shenzhen	1.0021	0.997	1.0051	1.0048	1.0000	1.0003
	Zhuhai	1.0566	1.0000	1.0566	1.0000	1.0008	1.0558
	Foshan	0.9914	0.9783	1.0134	1.0152	1.0000	0.9983
	Heyuan	1.0157	1.0047	1.0110	0.9811	1.0073	1.0230
	Huizhou	1.0082	0.9960	1.0122	1.0112	0.9999	1.0011
	Shanwei	1.0507	1.0413	1.0091	0.9906	0.9994	1.0193
	Dongguan	1.0133	0.9854	1.0283	1.0272	1.0000	1.0011
	Zhongshan	1.0058	0.9954	1.0104	1.0098	1.0000	1.0006
	Jiangmen	1.0067	0.9882	1.0188	1.0227	1.0000	0.9962
	Yangjiang	1.0084	0.9883	1.0203	1.0183	0.9988	1.0032
	Zhaoqing	0.9799	0.9683	1.0120	0.9665	1.0044	1.0424
	Qingyuan	0.9953	0.9593	1.0375	1.0373	0.9984	1.0018
	Yunfu	1.0143	0.9847	1.0300	1.0275	0.9987	1.0038

End of Table A1

Urban agglomerations	City	*MLPI*	*MLEFFCH*	*MLTECH*	*MLMATECH*	*MLOBTECH*	*MLIBTECH*
Yangtze River Delta	Shanghai	0.9858	0.9519	1.0357	1.0369	1.0000	0.9988
	Nanjing	1.0003	0.9598	1.0422	1.0224	1.0152	1.0041
	Wuxi	1.0073	0.9606	1.0486	1.0428	1.0039	1.0016
	Changzhou	1.0012	0.9676	1.0348	1.0307	1.0001	1.0039
	Suzhou	0.9914	0.9532	1.0400	1.0381	1.0016	1.0003
	Nantong	1.0060	0.9743	1.0325	1.0293	0.9999	1.0032
	Yancheng	1.0010	0.9703	1.0317	1.0302	0.9956	1.0059
	Yangzhou	1.0190	0.9809	1.0388	1.0313	1.0012	1.0061
	Zhenjiang	1.0132	0.9771	1.0369	1.0296	1.0078	0.9993
	Taizhou	1.0072	0.9821	1.0255	1.0238	0.9977	1.0039
	Hangzhou	0.9999	0.9668	1.0342	1.0244	1.0081	1.0014
	Ningbo	0.9858	0.9601	1.0267	1.0248	1.0001	1.0018
	Jiaxing	0.9946	0.9626	1.0332	1.0292	1.0039	1.0000
	Huzhou	1.0049	0.9649	1.0415	1.0404	0.9997	1.0013
	Shaoxing	0.9987	0.9669	1.0328	1.0278	1.0070	0.9979
	Jinhua	0.9899	1.0131	0.9771	0.9656	1.0134	0.9985
	Zhoushan	1.0250	0.9584	1.0695	1.0525	1.0056	1.0105
	Taizhou	1.0032	0.9729	1.0311	1.0250	1.0041	1.0019
	Hefei	1.0605	1.0053	1.0549	1.0546	1.0019	0.9983
	Wuhu	1.0281	0.9837	1.0451	1.0373	1.0035	1.0040
	Maanshan	0.9924	0.9575	1.0364	1.0259	1.0074	1.0028
	Tongling	1.0125	0.9741	1.0394	1.0379	1.0029	0.9986
	Anqing	1.0264	0.9952	1.0314	1.0250	1.0018	1.0044
	Chuzhou	1.0020	0.9872	1.0150	0.9877	0.9989	1.0288
	Chizhou	0.9935	0.9719	1.0223	1.0315	1.0005	0.9906
	Xuancheng	0.9961	0.9537	1.0444	1.0436	0.9996	1.0011
Beijing-Tianjing-Hebei	Mean	1.0148	0.9966	1.0183	1.0152	1.0022	1.0009
Pearl River Delta	Mean	1.0108	0.9896	1.0214	1.0103	1.0006	1.0104
Yangtze River Delta	Mean	1.0055	0.9719	1.0346	1.0286	1.0031	1.0026
Overall	Mean	1.0088	0.9817	1.0276	1.0208	1.0022	1.0044