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Interfaces with Other Disciplines

Analysis on China's eco-innovations: Regulation context, intertemporal change and regional differences

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ABSTRACT

Eco-innovation is recognized as a determinant of success or failure of environmental protection efforts in the long run. This paper attempts to examine China's eco-innovation gains in response to the energy saving and emissions reduction (ESER) policy enforced during 2006–2010. We first construct an integrated analysis framework to evaluate the changes of energy and environmental performance used as the proxy of eco-innovation, and then the intertemporal change of China's eco-innovation gains as well as the regional differences is investigated. The results indicate that China had accelerated its process of eco-innovations during 2006–2010 when a series of ESER policies were enforced. The developments and wide adoptions of advanced energy saving and environmentally friendly technologies serve as the primary driving forces, while upgrading management skills and organizational designs contribute relatively little. Furthermore, the realizing paths of cross-region eco-innovations in China are obviously discrepant.

1. Introduction

To relieve the constraints of energy shortage and environmental deterioration to China's sustainable economic growth, great efforts have been taken by the central government to enforce energy saving and emissions reduction (ESER) during the 11th five-year plan (FYP). By the end of 2010, China had decreased its energy intensity by nearly 20 percentage points compared with 2005 levels, and the total amount of sulphur dioxide (SO_2) and chemical oxygen demand (COD) emissions in this developing country have respectively been reduced by 14.29 percent and 12.45 percent during the same period. However, as the low hanging fruits have been picked over, the marginal costs for further energy saving and emissions reduction efforts are increasing rapidly. The prospect of China's energy and environmental situations in the following several decades are still unknown and an effective long-term mechanism for promoting ESER practices is urgently required.

Eco-innovation, which plays a crucial role in decoupling China's rapid economic growth from its resource consumptions and environmental pollutions, is considered as one of the most important determinants of success or failure of energy saving and environmental protection practices in the long run (Jaffe, Newell, & Stavins, 2002). In general, eco-innovation is defined as the process of developing or implementing new products, processes or organizational arrangements which significantly decrease environmental impact but provide increased competitiveness of the users (Fussler & James, 1996; Kemp & Pearson, 2008; OECD, 2009). Yet due to the existence of dual externalities including environmental externalities and knowledge spillovers, firms lack the incentives to invest voluntarily in eco-innovation activities (Jaffe, Newell, & Stavins, 2003). In this context, some normative analysis suggest that public policies on energy saving and environmental protection, when appropriately designed, can stimulate the innovation and adoption of environmental-friendly technologies (López-Gamero, Claver-Cortés, & Molina-Azorín, 2009; Perino & Requate, 2012).

Up to now, numerous studies focus on the actual effects of environmental policies on eco-innovation (see Kemp & Pontoglio, 2011 and Popp, 2010a for a review). The dominant view insists that policy instruments designed to improve environmental quality can encourage environmentally-friendly technological change. On the one hand, policy instruments internalizing environmental externalities change the direction of technological change towards environmental innovations. Based on induced innovation hypothesis proposed by Hicks (1932), early studies found that some emissions reduction policies such as carbon/energy tax drive up the prices of fossil fuels relative to other inputs, and then induce the development of

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energy-efficient technologies. For example, Newell, Jaffe, and Stavins (1999) demonstrate that there exist a positive relationship between energy price and the improvement of energy efficiency in home appliances such as air conditioners and gas water heaters. Popp (2002) finds a long-term positive elasticity of energy patenting regarding energy price, i.e., patents on energy-efficiency technologies increase when the price of energy goes up. Kumar and Managi (2009) also verified that substantial oil price-induced technological progress at the world level has emerged when long-term oil prices are rising. More recently, Lukas and Welling (2014) point out that the European Union emissions trading scheme creates financial incentives for companies to invest in climate-friendly innovations in order to reconcile economic efficiency with ecological efficiency.

On the other hand, wide adoption of existing leading environmentally friendly technologies is another important pathway for firms' eco-innovation gains, and well-designed environmental policies that are linked to market conditions and to firms' technological capabilities can effectively accelerate this process. Jaffe, Newell, and Stavins (2005) indicate that energy conservation tax credits or technology subsidies speed the adoption of new environmental technologies by decreasing uncertain returns on investment for firms. Taylor, Rubin, and Hounshell (2005) find that stricter SO_2 emissions standards force the wide utilization of desulfurization facilities. Recently, Popp (2010b) points out that firms tend to adopt newer post-combustion control techniques to save costs in response to increasing regulatory stringency.

As we summarize from the existing literature that a majority of previous empirical studies focus on the effects of a single environmental policy instrument on a specific type of eco-innovations in a given technological field. But in practice, a portfolio of policy instruments including command-and-control measures (such as technology-based standards) and market-based policy instruments (such as environmental tax and energy-saving subsidies) is employed synchronously to address all kinds of environmental problems in different circumstances (Bennear & Stavins, 2007). These environmental instruments create incentives or constraints for the development and adoption of different eco-innovation types through different channels (Kesidou & Demirel, 2012; Triguero, Moreno-Mondéjar, & Davia, 2013). In many cases, there often exists very complicated interaction effects among these policy instruments (Zhang, Zhang, Liu, & Bi, 2013), thus it is generally difficult to distinguish the eco-innovation effect of one environmental policy instrument from another. In this context, a more comprehensive analysis framework is indispensable to investigate the actual eco-innovation effects of the combination of various environmental instruments from a macro perspective.

In this paper, we attempt to examine the integrated eco-innovation effects of China's energy saving and emissions reduction policy enforced during the 11th FYP. Unlike previous studies that used environmental R&D investment or environmental patents as the proxy of eco-innovation, this paper constructs a productivity index specified at energy saving and emissions reduction for eco-innovation measurement as suggested by Arundel and Kemp (2009). The advantages of employing this index include two aspects. On the one hand, it can capture the comprehensive effects of all kinds of eco-innovation practices including technological and non-technological types. On the other hand, the productivity index is easy to be further decomposed into several components so that we can identify the channels through which production units conduct their eco-innovations. The rest of this paper is organized as follows: Section 2 describes the definition of eco-innovations and selects a proper indicator for its measurement, Section 3 elaborates the methodology used in this study, Section 4 reports the actual eco-innovation effects of China's ESER policy along with the pathway diversities among 30 administrative provinces, Section 5 concludes the paper and puts forward some useful policy implications.

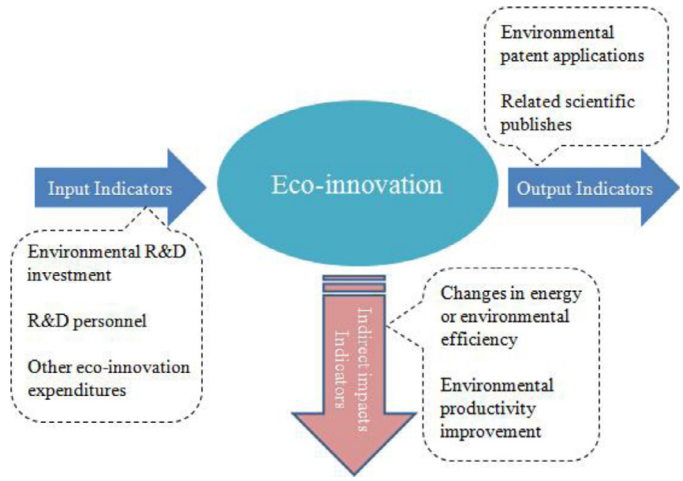


Fig. 1. Alternative measurement indicators for eco-innovation.

2. Definition of eco-innovation and its measurement

2.1. Definition of eco-innovation

In recent years, eco-innovation firstly proposed by Fussler and James (1996) has acquired increasing attention from policy makers and scholars worldwide. Due to the involvement of interdisciplinarity in sociology, economics and ecology, different definitions for eco-innovation have emerged without a standardized statement (Kemp & Pearson, 2008; OECD, 2009; Rennings, 2000; EIO, 2013). This paper applies the conception illustrated by OECD (2009) as follows:

"*The creation or implementation of new or significantly improved products (goods and services), process, marketing methods, organizational structure and institutional arrangements which – with or without intent – lead to environmental improvements compared to relevant alternatives*".

Three distinguishing characteristics can be drawn from the above definition of eco-innovation: (1) *Universality*: there are many types of eco-innovation practices ranging from technological dimensions to social and institutional ones, such as eco-products, eco-processes or eco-organizations (Triguero et al., 2013). Moreover, it is not just limited to the traditional innovation introduced by Schumpeter (1934), but encompasses the diffusion of already available environmentally-friendly products, processes, or organizations. (2) *Effectiveness*: it underlines the real environmental effects of all types of innovation activities, regardless of whether they were intended to be "ecological" or not. Eco-innovation gains can thus result from firms' other economic activities such as increasing market share or reducing production costs, although these practices are not predominantly motivated by environmental concerns (Horbach, Rammer, & Rennings, 2012). (3) *Relativity*: compared to the previous technology (or organization), the new one improves the environmental performance of adopters.

2.2. Measurement for eco-innovation

Eco-innovation is difficult to be fully and directly assessed due to its intrinsic "eco" element. Hence several alternative indicators are usually employed by existing empirical studies. Arundel and Kemp (2009) offer a review on available measurement indicators for eco-innovation and group them into three categories as shown in Fig. 1.

As the main sources of technological eco-innovations, input measures such as environmental R&D expenditures or personnel have been given a priority to the measurement of eco-innovation (Demirel & Kesidou, 2011; Popp & Newell, 2012). However, this type of indicators may be biased when there are inefficient R&D investments (Kumar & Managi, 2009). As an alternative, some output indicators

such as the number of successful environmental-related patent applications or scientific publications, have been applied widely in previous empirical literatures (Johnstone, Hascic, & Popp, 2010; Marin, 2014; Noailly, 2012; Popp, 2006). Yet the limitations of these indicators for the measurement of technological eco-innovations have also been pointed out in the existing literatures (Arundel & Kemp, 2009; Marin, 2014). For instance, patent applications usually overestimate technological innovation when patents have not been commercialized successfully. Furthermore, neither input nor output indicators cover organizational and service eco-innovations since these innovations are often not listed in government R&D expenditure budget, and also not patented.

To gain a more comprehensive picture of eco-innovation, some scholars suggest that the change in eco-efficiency or environmental productivity is a feasible alternative since the final effects of eco-innovation practices are embodied in the improvements of eco-efficiency performance or environmental productivity (Arundel & Kemp, 2009; Kumar & Managi, 2009). In contrast to the input and output indicators, these indirect measurements can capture the actual and aggregated effects of all eco-innovation practices including technological and non-technological ones. In this regards, the measurement of eco-productivity has attracted more and more attention. Mahlberg and Sahoo (2011) assess eco-productivity performance of 22 OECD countries using the directional Russell measure of inefficiency. Picazo-Tadeo, Gómez-Limón, and Beltrán-Esteve (2014) measure environmental productivity of EU-28 member states and decompose it as the result of eco-efficiency change and environmental technical change (or eco-innovation).

Unlike Picazo-Tadeo et al. (2014) that treat eco-innovation as a component of environmental productivity, in this paper we consider the intertemporal change of entities' energy and environmental performance as the proxy of technological and non-technological eco-innovation. To construct this productivity index, we define a three-dimensional directional distance function which incorporates the targets of economic growth, energy conservation and emissions reduction in a common analysis framework.

Another important merit of employing productivity index is that we can further identify the pathway through which one entity obtains its eco-innovation by decomposing its productivity change. The developed indicator in this paper can mainly be decomposed into two components: the purely technological eco-innovation represented by the shift of energy saving and environmental friendly technologies (EET) frontier, and the technical efficiency change measured by the movement towards the frontier of EET. The former mainly results from the following activities: (1) the development and successful commercialization of advanced energy and environmental technologies, such as technology breakthroughs in energy conservation and pollution control, new green products, cleaner process technologies and handling techniques (Kemp & Pontoglio, 2011); (2) the wide diffusions of best-practice eco-technologies; and (3) the commercial process of a previously existing technical idea that was never used (Newell, Jaffe, & Stavins, 2006). In contrast, the technical efficiency change captures the catch-up effect of the entity under the frontier of EET towards the corresponding best practice, which can mainly be attributed to: (1) organizational and institutional innovations that facilitate successfully economic production compatible with energy saving and emissions reduction, such as the establishment and improvement of environmental management system; and (2) the diffusions of management skills or technical experiences related to the leading energy saving and environmental friendly technologies (Briec, Peypoch, & Ratsimbanierana, 2011).

3. Methodology

In this section we first define a non-radial directional distance function (NDDF) in a three-dimensional space. Then we use the NDDF to construct the productivity index of EET. Finally, the calculation of the proposed indicators is presented.

3.1. Non-radial directional distance function

We consider a multi-input and multi-output production technology, by which one production unit uses a vector of K non-energy inputs $\boldsymbol{x} \in R_+^K$, and a vector of H energy inputs $\boldsymbol{e} \in R_+^H$ to produce a vector of M desirable outputs $\boldsymbol{y} \in R_+^M$ and a vector of G undesirable outputs $\boldsymbol{u} \in R_+^G$. The production technology can be defined as follow:

$$T = \{(\boldsymbol{x}, \boldsymbol{e}, \boldsymbol{y}, \boldsymbol{u}) : (\boldsymbol{x}, \boldsymbol{e}) \text{canproduce}(\boldsymbol{y}, \boldsymbol{u})\}. \tag{1}$$

For each time period t, the production possibility set T summarizes the set of all feasible input and output vectors (Briec & Kerstens, 2009). Taking Beijing, a decision making unit (DMU) in this study as an example: in 2010, it used a total amount of 2352 billion Yuan of capital, 13.2 million labour forces and 69.5 million tonnes of standard coal equivalent of energy to produce 752 billion Yuan of GDP. Meanwhile, 115 thousand tonnes of SO_2 was generated and emitted. In addition, the production technology T satisfies a set of axioms discussed in Färe and Primont (1995). Being similar to the conventional environmental production technology, the strong disposability for inputs and desirable outputs as well as the weak disposability for undesirable outputs are also assumed.

Obviously, Eq. (1) is a general expression of the production technology, which describes all the feasible economic activities in favour of energy saving and environment protection or not. Thus it is difficult to directly distinguish a specific production behaviour aiming at energy conservation or emissions reduction. Alternatively, the directional distance function is widely used to address this issue by setting different direction vectors (Mahlberg & Luptacik, 2014; Picazo-Tadeo, Beltrán-Esteve, & Gómez-Limón, 2012). For example, Zhou, Ang, and Wang (2012) recognize the energy saving and/or environmentally friendly production activities applying non-radial directional distance functions. Along with this line, we define a three-dimensional directional distance function by setting a directional vector $\boldsymbol{g} = (-g_e, g_y, -g_u)$ $(g \neq 0)$ to identify the production behaviour in favour of energy saving and emissions reduction. Considering that China is a developing country holding about 200 million impoverished population, promoting economic growth and eliminating poverty is still given the first priority. Thus the normalized weight vector is taken as (1/4, 1/2, 1/4) throughout this study. Then the non-radial directional distance function can be defined as:

$$\begin{aligned}\overrightarrow{D}(x, e, y, u; g) &= \sup\left\{\left(\tfrac{1}{4}\alpha + \tfrac{1}{2}\beta + \tfrac{1}{4}\gamma\right) : (x, e - \alpha \cdot g_e, y \right. \\ &\quad \left. + \beta \cdot g_y, u - \gamma \cdot g_u) \in T\right\}\end{aligned} \tag{2}$$

where $\overrightarrow{D}(x, e, y, u; g)$ satisfies several properties of directional distance function (More derivations can be found in Zhou et al. (2012)). Clearly, this distance function determines the benchmark of EET, where producers attain the maximum of desirable outputs $y + \beta \cdot g_y$ and emit the least of undesirable outputs $u - \gamma \cdot g_u$ using the minimum of energy inputs $e - \alpha \cdot g_e$ along with a given amount of non-energy inputs.

The directional vector $\boldsymbol{g}$ ensures specific paths of contraction or expansion for energy inputs, undesirable and desirable outputs towards the frontier of EET. The choice of the direction vector constitutes a key issue for the directional distance function (Chambers, Chung, & Färe, 1998). Some empirical studies consider simple cases with $g = (-1^n, 1, 0)$, where 1^n is the n-dimensional unit vector. In this context, the computed distance functions are sensitive to the measurement units and magnitude of the variables (Picazo-Tadeo, Reig-Martínez, & Hernández-Sancho, 2005). Alternatively, the special directional vector chosen at the realized input–output vector to measure technical efficiency defined in the Farrell proportional distance function, has also been widely used in empirical literature, such

as Chung, Färe, and Grosskopf (1997), and Oh and Heshmati (2010). Compared to the simple direction vector, a significant advantage of the specific-directional vector is units' invariance (Adler & Yazhemsky, 2010; Lovell & Pastor, 1995), that is, the values of the distance function are independent of measurement units for inputs or outputs variables. In this study, we choose the specific-directional vector $g = (-e, y, -u)$. Accordingly, the coefficients α and γ are the proportions of maximum possible decrease in energy input and undesirable outputs towards the frontier, respectively; while β is the maximum possible ratio of increase in desirable outputs. They take values larger than or equal to zero. The value of the distance function $\frac{\alpha}{4} + \frac{\beta}{2} + \frac{\gamma}{4}$ represents the maximal distance of the observed combination regarding three variables for one entity from the EET frontier. The larger this value takes, the wider the gap between its current technology and the EET frontier.

Note that Eq. (2) attaches more importance to economic growth than energy saving and emissions reduction. This assumption is well consistent with China's current development situation with the first priority of economic growth and eliminating poverty. Of course, the normalized weight vector should be changed towards more ecological awareness, for instance, (1/3, 1/3, 1/3), after a certain industrial development is achieved by this developing country. In this context, researchers would treat the three variables equally. As a result, an additional advantage of this methodological approach is that it allows incorporating into the model the preferences of researchers or policymakers by setting different schemes for the weightings vector.

3.2. Productivity index of EET and its decomposition

We construct the productivity index of EET by substituting NDDF for the directional distance function in Luenberger productivity indicator developed by Chambers, Färe, and Grosskopf (1996) and rename it *EETPI*. To avoid the impact of arbitrarily employing a reference technology on the final result, we define EETPI $^{t,t+1}$ as:

$$\begin{aligned}\mathrm{EETPI}^{t,t+1} &= \frac{1}{2}(\mathrm{EETPI}^{t} + \mathrm{EETPI}^{t+1}) \\ &= \frac{1}{2}\Big[\vec{D}^{t}(x^t, e^t, y^t, u^t; g^t) - \vec{D}^{t}(x^{t+1}, e^{t+1}, y^{t+1}, u^{t+1}; g^{t+1}) \\ &\quad + \vec{D}^{t+1}(x^t, e^t, y^t, u^t; g^t) - \vec{D}^{t+1}(x^{t+1}, e^{t+1}, y^{t+1}, u^{t+1}; g^{t+1})\Big]\end{aligned} \tag{3}$$

where $\vec{D}^{t}(x^t, e^t, y^t, u^t; g^t)$ and $\vec{D}^{t+1}(x^{t+1}, e^{t+1}, y^{t+1}, u^{t+1}; g^{t+1})$ are contemporaneous NDDFs capturing the distance of the observed data from current EET frontier. $\vec{D}^{t}(x^{t+1}, e^{t+1}, y^{t+1}, u^{t+1}; g^{t+1})$ and $\vec{D}^{t+1}(x^t, e^t, y^t, u^t; g^t)$ refer to mixed period NDDFs. The former compares the observed data of one producer at period $t + 1$ to the technology frontier at period t, and the latter compares the observed data of producers at period t to the best practice at period $t + 1$. Here $\mathrm{EETPI}^{t,t+1}$ measures the rate of change in energy and environmental performance. $\mathrm{EETPI}^{t,t+1} > 0$ indicates productivity growth of EET implying that production units have undertaken more eco-innovation activities in period $t + 1$ compared to period t. On the contrary, $\mathrm{EETPI}^{t,t+1} < 0$ shows productivity decline for one production unit; that is, instead of conducting eco-innovation activities, the producers use some technologies not friendly to energy conservation and environmental protection in period $t + 1$. It is worthwhile to note that there may exist "spurious" productivity decline since the directional distance function measures the relative distance of the observed input–output combination from the frontier. In spite of conducting eco-innovation activities, $\mathrm{EETPI}^{t,t+1}$ of a production unit can still be lower than zero if its speed is slower than that of the frontier technology. $\mathrm{EETPI}^{t,t+1} = 0$ indicates a relative stagnation in the productivity level of EET for producers.

As discussed in Section 2, the productivity changes of EET for a producer can be decomposed into two components: technical change (EETTch) as a result of purely technological eco-innovations, and efficiency change (EETEch) resulting from the improvements of managerial skills and/or institutional environment related to existing eco-technologies as follows:

$$\mathrm{EETPI}^{t,t+1} = \mathrm{EETTch}^{t,t+1} + \mathrm{EETEch}^{t,t+1} \tag{4}$$

Where,

$$\begin{aligned}&\mathrm{EETTch}^{t,t+1} \\ &= \frac{1}{2}\Big[\vec{D}^{t+1}(x^{t+1}, e^{t+1}, y^{t+1}, u^{t+1}; g^{t+1}) - \vec{D}^{t}(x^{t+1}, e^{t+1}, y^{t+1}, \\ &\quad u^{t+1}; g^{t+1}) + \vec{D}^{t+1}(x^t, e^t, y^t, u^t; g^t) - \vec{D}^{t}(x^t, e^t, y^t, u^t; g^t)\Big]\end{aligned} \tag{5}$$

$$\mathrm{EETEch}^{t,t+1} = \vec{D}^{t}(x^t, e^t, y^t, u^t; g^t) - \vec{D}^{t+1}(x^{t+1}, e^{t+1}, y^{t+1}, u^{t+1}; g^{t+1}) \tag{6}$$

$\mathrm{EETTch}^{t,t+1}$ measures the relative magnitude of technological innovations in the direction $\boldsymbol{g}$ throughout periods t and $t + 1$. $\mathrm{EETTch}^{t,t+1} > 0$ indicates eco-innovation activities enable a shift of the production possibility frontier of EET towards lower energy and/or emissions intensities. $\mathrm{EETTch}^{t,t+1} < 0$ reflects the regress of EET frontier, that is, the best-practice technology in period $t + 1$ produces lower energy and environmental performance compared to that in period t. $\mathrm{EETTch}^{t,t+1} = 0$ shows there is no change in the frontier.

$\mathrm{EETEch}^{t,t+1}$ is the change of distances between the used technologies and the current frontier technology throughout periods t and $t + 1$, which captures the speed by which producer moves towards the current technology frontier, namely catch-up or fall-behind effect. For an entity, EETEch $^{t,t+1} > 0$ implies an improvement of managerial skills and/or institutional environment in terms of eco-innovation; $\mathrm{EETEch}^{t,t+1} < 0$ shows its technological level is farther from the frontier technology. $\mathrm{EETEch}^{t,t+1} = 0$ may occur in two cases. On the one hand, if a production unit has been operating on the EET frontier and improves its current technology level only through technological innovation, then its $\mathrm{EETEch}^{t,t+1}$ would be equal to zero. On the other hand, $\mathrm{EETEch}^{t,t+1} = 0$ occurs when the distances deviating from the frontier between two periods are constant.

3.3. Calculation of $EETPI^{t,t+1}$ and its two components

According to Eqs. (3), (5) and (6), the values of $\mathrm{EETPI}^{t,t+1}$, $\mathrm{EETTch}^{t,t+1}$ and $\mathrm{EETEch}^{t,t+1}$ can be computed. In this analysis, nonparametric data envelopment analysis (DEA) approach is employed to avoid the misspecification of the functional form often confounded by econometrics methods. Up to now, there are several alternative techniques in the DEA-related literature to construct the production frontier of panel data as discussed in Fried, Knox-Lovell, and Schmidt (2008), including contemporaneous DEA, windows analysis technique, sequential DEA and a single grand frontier. Given that the technologies developed in previous periods are still feasible in the following years, this study employs sequential DEA to construct the benchmark technology based on all previous observations of consecutive periods. The distinct advantage of this technique is that it eliminates the possibility of registering any technical regress by definition (Shestalova, 2003), and this choice is more justified when we are studying the technology of a macro economy being the aggregate of all industrial sectors (Oh & Heshmati, 2010).

Then the benchmark at period t should be $\overline{T}^t = T^1 \cup T^2 \cup \ldots \cup T^t$, where T^t derived from the observed data of a set of N entities at time

t can be written as:

$$T^t\left(x^t, e^t, y^t, u^t\right) = \left\{\left(x^t, e^t, y^t, u^t\right) : \left(x^t, e^t\right)\text{can produce}\left(y^t, u^t\right)\right\}$$
$$= \left\{\left(x^t, e^t, y^t, u^t\right) : \sum_{i=1}^{N} z_i^t x_{ki}^t \le x_{ki}^t, \sum_{i=1}^{N} z_i^t e_{hi}^t \le e_{hi}^t, \right.$$
$$\left. \sum_{i=1}^{N} z_i^t y_{mi}^t \ge y_{mi}^t, \sum_{i=1}^{N} z_i^t u_{gi}^t = u_{gi}^t, z_i^t \ge 0, i = 1, \ldots, N\right\} \quad (7)$$

where z_i^t is the weight assigned to corresponding observation. The inequality constraints on the inputs and economic outputs as well as the equality constraint on the undesirable outputs reflect their strong and weak disposability, respectively. As to the construction of production frontier for a set of DUMs, please see Chapter 6 in Coelli, Rao, O'Donnell, and Battese (2005) for more detail.

For the ith producer at time t, its contemporaneous distance function can be calculated by solving the following linear programming:

$$\vec{D}^t(x^t, e^t, y^t, u^t; g^t)$$
$$= \max\left(\frac{1}{4}\cdot\frac{1}{H}\sum_{h=1}^{H}\alpha_{hi}^t + \frac{1}{2}\cdot\frac{1}{M}\sum_{m=1}^{M}\beta_{mi}^t + \frac{1}{4}\cdot\frac{1}{G}\sum_{g=1}^{G}\gamma_{gi}^t\right)$$
$$s.t. \quad \sum_{s=1}^{t}\sum_{i=1}^{N} z_i^s e_i^s \le e_{hi}^t - \alpha_{hi}^t e_{hi}^t, \quad h = 1, \ldots, H$$
$$\sum_{s=1}^{t}\sum_{i=1}^{N} z_i^s x_{hi}^s \le x_{ki}^t, k = 1, \ldots, K$$
$$\sum_{s=1}^{t}\sum_{i=1}^{N} z_i^s y_i^s \ge y_{mi}^t + \beta_{mi}^t y_{mi}^t, \quad m = 1, \ldots, M$$
$$\sum_{s=1}^{t}\sum_{i=1}^{N} z_i^s u_{gi}^s = u_{gi}^t - \gamma_{gi}^t u_{gi}^t, \quad g = 1, \ldots, G$$
$$z_i^s, \alpha_{hi}^t, \beta_{mi}^t, \gamma_{gi}^t \ge 0, \text{for all } i, h, m, g; \quad i = 1, \ldots, N \quad (8)$$

The intertemporal distance function $\vec{D}^t(x^{t+1}, e^{t+1}, y^{t+1}, u^{t+1}; g^{t+1})$ for the ith entity can be computed from the following linear programming:

$$\vec{D}^t(x^{t+1}, e^{t+1}, y^{t+1}, u^{t+1}; g^{t+1})$$
$$= \max\left(\frac{1}{4}\cdot\frac{1}{H}\sum_{h=1}^{H}\alpha_{hi}^{t+1} + \frac{1}{2}\cdot\frac{1}{M}\sum_{m=1}^{M}\beta_{mi}^{t+1} + \frac{1}{4}\cdot\frac{1}{G}\sum_{g=1}^{G}\gamma_{gi}^{t+1}\right)$$
$$\text{s.t.} \quad \sum_{s=1}^{t}\sum_{i=1}^{N} z_i^s e_i^s \le e_{hi}^{t+1} - \alpha_{hi}^{t+1} e_{hi}^{t+1}, \quad h = 1, \ldots, H$$
$$\sum_{s=1}^{t}\sum_{i=1}^{N} z_i^s x_{hi}^s \le x_{ki}^{t+1}, \quad k = 1, \ldots, K$$
$$\sum_{s=1}^{t}\sum_{i=1}^{N} z_i^s y_i^s \ge y_{mi}^{t+1} + \beta_{mi}^{t+1} y_{mi}^{t+1}, \quad m = 1, \ldots, M$$
$$\sum_{s=1}^{t}\sum_{i=1}^{N} z_i^s u_{gi}^s = u_{gi}^{t+1} - \gamma_{gi}^{t+1} u_{gi}^{t+1}, \quad g = 1, \ldots, G$$
$$z_i^s, \alpha_{hi}^t, \beta_{mi}^t, \gamma_{gi}^t \ge 0, \ for \text{ all } \ i, h, m, g; i = 1, \ldots, N \quad (9)$$

Here $\vec{D}^t(x^{t+1}, e^{t+1}, y^{t+1}, u^{t+1}; g^{t+1})$ denotes the distance of the observation in period $t+1$ from the production possibility frontier in period t. Likewise, $\vec{D}^{t+1}(x^t, e^t, y^t, u^t; g^t)$ can also be calculated by solving a similar linear programming.

4. Results and discussions

The study sample of this paper contains 30 inland administrative provinces in China. Due to the absence of basic data on energy consumption, Tibet is not included in current study. Moreover, in order to investigate the eco-innovation gains in response to the enforcement of ESER policy during the 11th FYP, the study period is set between 2000 and 2010.

4.1. Data descriptions

The identification and selection of the input and output variables to be used in DEA context play key roles in the validity and credibility of the results of the efficiency assessment. To increase the discriminating power of DEA model, the number of decision-making units should be more than 3 $(m + s)$, where m stands for the number of inputs and s for the number of outputs (Friedman & Sinuany-Stern, 1998). Subsequently, Dyson et al. (2001) pointed out that the number of units should be at least $2m \times s$ based on a suggested 'rule of thumb'. In this paper, we investigate the production process of 30 administrative provinces in China with three inputs (Capital, Labour, and Energy), one desirable output (GDP) and one undesirable output (SO_2), which satisfies the above-mentioned rules theoretically.

Here total energy consumption, employed persons and capital stock serve as the inputs of energy, labour and capital, respectively. The desirable output is measured by real GDP, and the undesirable output is represented by SO_2 emissions. The basic data on cross-region total energy consumption can be directly obtained from China Energy Statistical Yearbooks (CESYs, 2004, 2006, 2011). The data on employed persons over the whole sample period excluding 2006 is collected from China Statistical Yearbooks (CSYs 2001–2006, 2008–2011), while the data in 2006 is acquired from China Regional Economics Statistical Yearbook (CRESY, 2007). Capital stock for each region is estimated using perpetual inventory method, and the real GDP is obtained from China Statistical Yearbooks (CSYs, 2001–2011) by deflating its nominal value with GDP deflator. Both real GDP and capital stock are measured with 2000 price levels. Data on regional SO_2 emissions are also collected directly from China Statistical Yearbooks (CSYs, 2001–2011).

4.2. Results and discussions

4.2.1. Intertemporal changes of China's eco-innovations

The results of productivity index concerning energy saving and environmentally friendly technologies (EETPI) for each administrative province as well as the whole country during 2001–2010 are reported in Table 1. The national weighted averages of EETPI are also listed taking the shares of regional GDP to the total amount of China as weights. The results indicate that EETPI at the national level had experienced frequent fluctuations during the whole studied period, which decreased gradually in the 10th FYP (2001–2005) with its mean value at 0.42 percent and increased sharply since 2006 with the mean value at 1.77 percent during the 11th FYP. The gap between the two periods is relatively larger compared to the national weighted average scenario.

The underlying reason for the declining energy and environmental performance during 2001–2005 mainly lies in: at the very beginning of the new century when China was in its rapid industrialization and urbanization processes, energy intensive sectors such as steel and cement in this developing country have gotten dramatic expansion since 2002 triggering very serious resource and environmental costs. For example, compared to the level of 2000, China's total energy consumption in 2005 had increased by more than 60 percent. And due to the soar of SO_2 emissions, more than one-third of China's territorial area suffers from acid precipitation.

Table 1
Cross-region productivity index of EET during 2001–2010.

Regions	2001/2000	2002/2001	2003/2002	2004/2003	2005/2004	2006/2005	2007/2006	2008/2007	20092008	2010/2009
Beijing	0.127	0.012	0.100	0.039	0.024	0.036	0.035	0.043	0.023	0.020
Tianjin	0.071	0.074	0.032	0.064	0.013	0.035	0.092	0.051	0.050	0.049
Hebei	0.012	−0.018	−0.005	0.015	0.020	0.019	0.025	0.016	0.008	0.015
Shanxi	0.000	0.013	0.007	0.006	−0.013	−0.015	0.009	−0.024	−0.069	−0.004
Inner Mongolia	0.001	−0.011	−0.053	−0.007	−0.008	0.002	0.006	0.004	−0.015	−0.019
Liaoning	0.126	0.128	0.099	−0.002	−0.017	0.007	0.027	0.013	0.027	0.020
Jilin	0.019	−0.006	0.004	0.021	0.015	−0.006	0.035	0.021	0.015	0.017
Heilongjiang	0.034	0.035	−0.006	0.055	0.022	0.020	0.091	0.021	0.010	0.020
Shanghai	0.019	0.025	0.020	0.018	0.005	0.000	0.030	0.028	0.000	0.022
Jiangsu	0.053	0.057	0.020	0.019	−0.005	0.037	0.064	0.048	0.037	0.023
Zhejiang	0.047	0.011	0.017	0.022	0.027	0.045	0.045	0.047	0.048	0.041
Anhui	0.014	0.018	0.000	0.008	−0.012	0.010	0.025	0.026	0.024	0.018
Fujian	0.015	0.000	−0.004	0.018	−0.045	0.052	0.043	0.031	0.029	0.039
Jiangxi	0.032	−0.021	−0.049	−0.020	−0.020	−0.003	0.028	0.047	0.033	0.033
Shandong	0.041	−0.046	0.019	0.031	0.006	0.018	0.057	0.034	0.021	0.017
Henan	0.006	−0.003	−0.013	−0.017	−0.021	−0.008	−0.001	0.021	0.011	0.005
Hubei	−0.020	−0.062	−0.067	−0.049	−0.020	−0.017	0.067	0.039	0.027	0.022
Hunan	−0.023	−0.027	−0.027	−0.006	−0.020	0.005	0.019	0.028	0.025	0.012
Guangdong	0.094	0.079	0.039	0.026	0.000	0.020	0.032	0.000	0.000	0.004
Guangxi	0.014	−0.008	−0.018	−0.019	−0.018	−0.011	−0.007	−0.005	−0.005	−0.002
Hainan	0.014	0.000	0.009	0.014	0.016	0.006	0.011	0.013	0.000	0.000
Chongqing	−0.033	0.014	−0.033	−0.037	−0.061	0.033	0.028	0.023	0.039	0.043
Sichuan	0.004	−0.002	−0.019	−0.001	0.003	0.008	0.020	0.006	0.033	0.030
Guizhou	−0.033	−0.023	−0.053	−0.003	0.044	0.021	0.045	0.022	−0.002	−0.008
Yunnan	0.017	−0.004	−0.019	−0.008	−0.034	−0.013	0.005	0.028	0.017	−0.002
Shanxi	−0.013	0.001	−0.022	−0.009	−0.010	0.012	0.052	0.028	0.021	0.008
Gansu	0.006	−0.020	−0.015	−0.005	−0.028	−0.015	−0.007	−0.032	−0.002	−0.003
Qinghai	−0.018	0.015	−0.096	−0.004	−0.043	0.008	0.048	0.038	−0.006	0.008
Ningxia	0.005	−0.023	−0.053	−0.027	−0.034	−0.008	0.008	0.008	−0.053	−0.026
Xinjiang	0.033	0.021	0.011	−0.022	0.005	0.000	0.027	0.028	0.004	0.003
National	0.022	0.008	−0.006	0.004	−0.007	0.010	0.032	0.022	0.012	0.013
Weighted average	**0.035**	**0.015**	**0.008**	**0.010**	**−0.003**	**0.015**	**0.037**	**0.025**	**0.018**	**0.018**

Note: EETPI at the national level are the arithmetic means of 30 administrative provinces. The shares of regional GDP to the total amount of the whole country are taken as weights when computing national weighted averages.

Table 2
Energy efficiency improvements of some energy intensive products.

Products	Unit	2005	2010	Reduction rates (percentage)
Coal-fired power generation	grams of coal equivalent per kilowatt hour	370	333	10.0
Raw steel	kilograms of coal equivalent per tonne	688	605	12.1
Cement	kilograms of coal equivalent per tonne	159	115	28.6
Ethylene	kilograms of oil equivalent per tonne	700	620	11.3
Synthetic ammonia	kilograms of coal equivalent per tonne	1636	1402	14.3
Aluminium ingots	kilowatt hour per tonne	14,633	14,013	4.2

Source: Yang, Patiño-Echeverri, Yang, and Williams (2015).

To alleviate the aggravating energy shortage situations, a series of compulsory policies and programs for energy saving have been implemented by the central government. For example, in order to upgrade China's industrial structure and restrict the pell-mell development of energy intensive industries, *Differential Electricity Pricing Policy* (DEPP) was promulgated and implemented ever since 2004, which imposes surcharges of electricity price on the "restricted" and "eliminated" categories of enterprisers subject to six (eight since September 2006) energy intensive industries (Chen, 2011). In the face of increasing energy using costs, the "green" awareness of business partners has been well strengthened. The enhancement of private customers' eco-awareness is to a large extent an individual process that's affected by some social factors, such as learning from friends, or following celebrities, and these individual interactions can be effectively oriented by extensive propagandas of necessity for ESER by all levels of governments. Moreover, some provincial and local governments have even voluntarily promulgated and implemented lots of ESER policies that were stricter than the counterparts promulgated by the central government. Thanks to the effective implementation of these policies, energy efficiency of some energy intensive industries has been greatly improved as shown in Table 2.

Simultaneously, lots of stringent environmental regulations have also been enforced to improve China's environmental quality. For example, due to the wide adoption of desulphurization facilities for coal-fired power plants, China had reduced its total SO_2 emissions by 14.29 percent during the 11th FYP in the face of more than 30 percent energy consumption increase. As a result, the ESER policy enforced during the 11th FYP had effectively enhanced China's energy saving and environmentally friendly technology levels, and these types of technological progress can be recognized as important sources for eco-innovation gains.

The potential stimulatory effects of ESER policy on China's eco-innovation can also be illustrated from regional perspective. Fig. 2 reports the mean values of cross-region productivity index of EET during the 10th and 11th FYPs, respectively. Overall, 24 of the 30 studied regions have achieved higher productivity scores in the 11th FYP than that in the 10th FYP, which indicates an overwhelming majority of administrative provinces in China conducted more eco-innovation activities in response to ESER policy. In particular, the encouragements of ESER policy for eco-innovations are more remarkable in 11 regions (including Fujian, Jiangxi, Henan, Hubei, Hunan, Chongqing, Sichuan, Guizhou, Yunnan, Shannxi, Qinghai) where productivity scores were

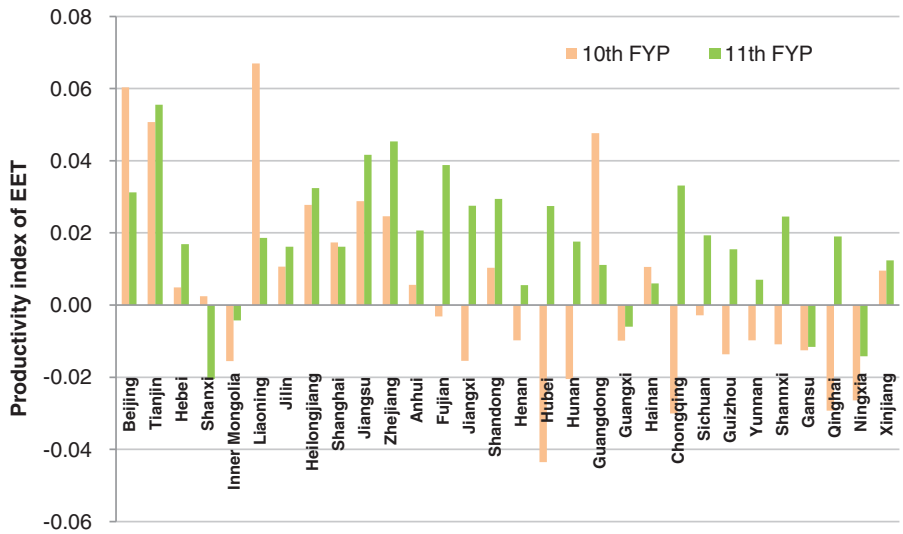
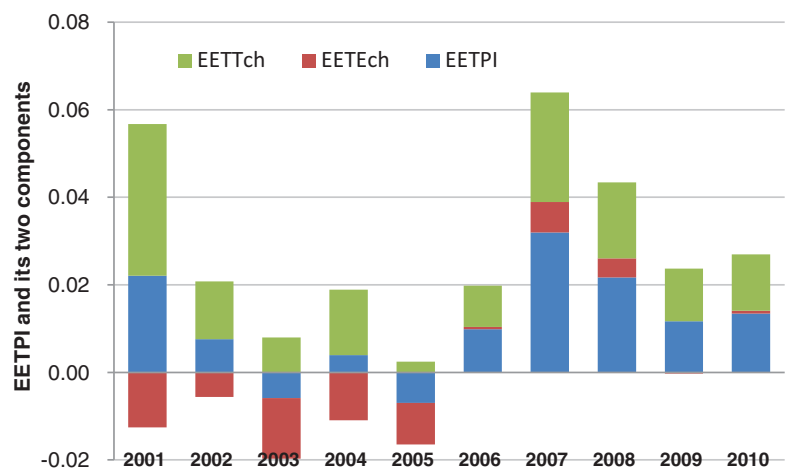


Fig. 2. Cross-region productivity scores of EET during the 10th and 11th FYPs.



Note: *EETPI* is the sum of EETTch and EETEch.

Fig. 3. Decomposition of EETPI during 2001–2010.

negative during the 10th FYP but turned positive in the 11th FYP. In contrast, productivity index of EET in some developed administrative provinces such as Beijing, Shanghai, and Guangdong in the 11th FYP are found to be lower than that in the 10th FYP. This does not necessarily mean eco-innovation activities were stagnant in these regions since their productivity scores are still larger than zero.

4.2.2. Path diversities of cross-region eco-innovations

As the potential boost of ESER policy for China's eco-innovation has been quantified from both national and regional levels, the sources of this stimulatory effect, i.e., the realizing path of China's eco-innovation gains, is another important topic worthwhile probing. To this end, we further decompose the national productivity index of EET into two components including EETTch and EETEch, and the result is reported in Fig. 3. Being highly consistent with the changing trend of EETPI, the EETTch component had also experienced frequent fluctuations during the whole studied period. Both in the 10th and 11th FYPs, the EETTch component acted as the determinant of China's energy and environmental performance changes. For example, of the average 1.77 percent national EETPI improvement during 2006–2010, the EETTch component (increase by 1.53 percent averagely) contributed more than 85 percent indicating that developments and wide adoptions of advanced energy saving and environmental friendlily technologies had made substantial contributions to China's eco-innovation gains.

This conclusion has been fully testified with China's practices for energy saving and emissions reduction. Given that outdated production capacities are generally considered as the synonyms of inefficient users of energy and also relatively larger emitters of pollutants (Geng, Lu, Wang, Gies,y, & Chen, 2010), lots of efficient and environmental friendly technologies have been widely adopted. It is reported that the proportion of power generating units with name plate capacity above 300 megawatt in China increased from 47 percent in 2005 to 69 percent in 2009. During the same period, the proportion of large blast furnaces with more than 1000 cubic meters of steel production capacity increased from 21 percent to 34 percent, and the percentage of cement production capacity from New Type Dry Process facilities rose from 56.4 percent to 72.2 percent (Yuan, Kang, Yu, & Hu, 2011). Besides, to achieve the specified target of reducing China's SO_2 emissions by 10 percent during the 11th FYP, more than 80 percent of China's coal-fired power generation units had been installed with desulphurization facilities, while this ratio was merely 12 percent by the end of 2005 (Yang, Yang, & Chen, 2011).

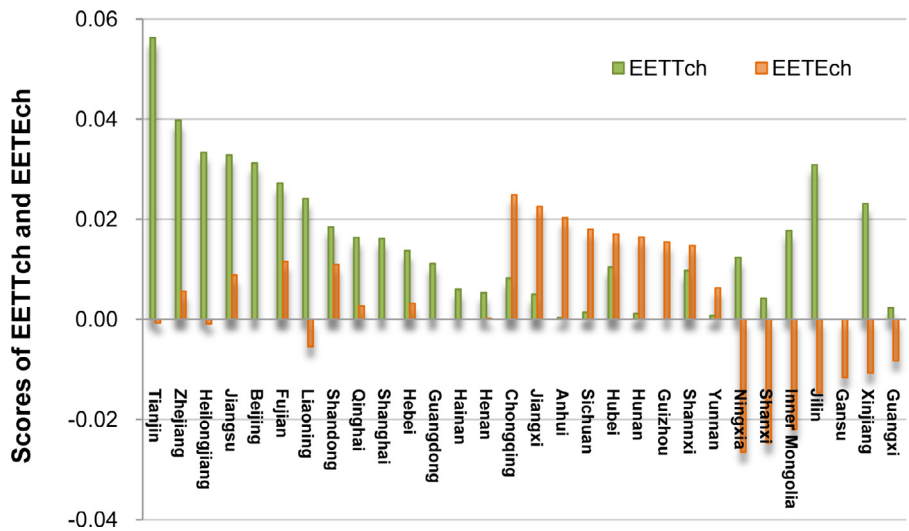


Fig. 4. Path diversities of China's regional eco-innovations during 2006–2010.

In contrast, the changing trend of EETEch was relatively monotonous which increased during 2001–2007 with the sole exception in 2003 and declined since 2008. The mean value of EETEch component was −1.1 percent during 2001–2005, and then it increased to 0.24 percent during 2006–2010. The change of EETEch implies that at the very beginning of the new century, technical progress was considered as the only way to conduct eco-innovations while little attention was paid to technical efficiency improvement so that it put off the eco-innovation practices to a certain extent. Subsequently, due to the stringent environmental regulations triggered by China's ESER policy, the potential of better management skills and organizational designs for eco-innovation has gradually been recognized and as a result, more and more importance was given to technical efficiency component in the 11th FYP.

We further shed some light on the path differences of China's cross-region eco-innovation gains during the 11th FYP and the results are shown in Fig. 4. In short, the realizing paths of cross-region eco-innovations can mainly be sorted into three categories according to the relative contribution of the two components. For the first category, EETTch plays a dominant role in regional eco-innovation activities while EETEch contributes very little. Most of the relatively developed administrative provinces such as Beijing, Tianjin, Shanghai, Guangdong, Jiangsu, and Zhejiang belong to this group.

For the second category, EETEch contributes much more to the improvement of EET productivity while impetus from the EETTch branch is very weak. Two-third of the six central administrative provinces (Jiangxi, Anhui, Hubei, and Hunan) along with nearly half of the western administrative provinces (Chongqing, Sichuan, Shannxi, Guizhou, and Yunnan) in China belong to this group. As to the third category, EETEch goes against EET productivity improvements while EETTch offsets this adverse impact to different extents. Some resources-based provinces such as Shanxi, Inner Mongolia, Ningxia and Xinjiang act as the typifiers.

5. Conclusions and policy implications

Eco-innovation plays an important role in decoupling China's total energy consumption and pollutant discharges from its rapid economic growth. In this paper, we try to investigate China's eco-innovation gains in response to the energy saving and emissions reduction (ESER) policy enforced during the 11th five year plan (FYP), and the path diversities among 30 administrative provinces have also been examined. With the main merit of capturing all kinds of knowledge accumulation related to eco-innovations, the productivity index of energy saving and environmentally friendly technology (EETPI) is selected as the measurement indicator. Moreover, decomposition of this proposed indicator allows us to identify the channels through which entities conduct their eco-innovation activities.

Three distinct conclusions can be drawn from the above analysis. First of all, China had accelerated its process of eco-innovations during the 11th FYP when a series of ESER policies were enforced. Specifically, the productivity scores of EET increased from 0.42 percent during the 10th FYP to 1.77 percent in the 11th FYP. Secondly, the developments and wide adoptions of leading energy saving and environmentally friendly technologies serve as the primary driving force of China's eco-innovation; while upgrading management skills as well as optimizing organization designs contributes little although the scores of technical efficiency component were overall in an increasing trend. Last but not the least, the realizing path of cross-region eco-innovation in China is obviously discrepant. For most of the developed regions and resources-based provinces, creations and implementations of purely eco-technologies play a more important role in eco-innovation gains. In contrast, enhancing management skills and organizational designs contributes more to the improvement of energy and environmental performance for the rest administrative provinces.

Several useful policy implications can be put forward from the above conclusions. First, given that EETEch component contributes relatively little to eco-innovation activities in most of the 30 studied administrative provinces, more attention should be paid to this relatively cost-saving approach. Second, since noticeable regional differences in terms of realizing paths for eco-innovation in China are observed during the 11th FYP, policymakers should formulate appropriate ESER policies for each administrative province according to its resource endowment, environmental capacity as well as the developmental stage rather than treat them uniformly. Only in this way, an effective policy system for solving China's energy and environmental dilemmas in the long-term can be well established.

At last, we would like to make certain discussions on the selection of decision making units (DMUs) and the methodological challenges. On the one hand, this paper employs DEA technique to evaluate the productivity scores of EET for China's 30 administrative regions following previous studies. According to Simar and Wilson (2008), application of any DEA model presumes that DMUs are independent. But in practice, regions influence each other by neighbourhood effects resulting from interregional trades and commuting, so these entities are economically not independent (Anselin, 1988; LeSage & Pace, 2009). In this case, the estimated results are biased if viewed

from long run performance point of views. Therefore, the conclusions based on DEA computation in this analysis can at best be considered to be short-run efficiency performance from practical point of view[1].

On the other hand, we encounter some cross-period programs without feasible positive solutions, i.e., infeasibilities, in our empirical computations (5.3 percent of the total programs). In general, infeasibilities of directional distance function may emerge in case of more than two output dimensions and non-null output direction vector (Briec & Kerstens, 2009). Up to now, most of previous studies deal with this drawback either by assigning a constant to infeasible observation or simply by omitting them from the computation of averages (Picazo-Tadeo et al., 2014). Besides, Färe, Grosskopf, and Pasurka (2001) tried to reduce the ratio of infeasibility with window analysis technique; and Mahlberg and Sahoo (2011) relax the assumption of non-negativity in the empirical computation of the directional distance functions. We deal with this problem by assigning a value equal to zero as mentioned in Picazo-Tadeo et al. (2014) because the computed results are not obviously improved when using the proposals by Färe et al. (2001) and Mahlberg and Sahoo (2011). Therefore, it is worthwhile to extend some follow-on works to eliminate the potential infeasibility in DEA model.

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