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Sources of energy productivity change in China during 1997-2012: A decomposition analysis based on the Luenberger productivity indicator

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Abstract: Given that different energy inputs play different roles in production and that energy policy decision making requires an evaluation of productivity change in individual energy input to provide insight into the scope for improvement of the utilization of specific energy input, this study develops, based on the Luenberger productivity indicator and data envelopment analysis models, an aggregated specific energy productivity indicator combining the individual energy input productivity indicators that account for the contributions of each specific energy input towards energy productivity change. In addition, these indicators can be further decomposed into four factors: pure efficiency change, scale efficiency change, pure technology change, and scale of technology change. These decompositions enable a determination of which specific energy input is the driving force of energy productivity change and which of the four factors is the primary contributor of energy productivity change. An empirical analysis of China's energy productivity change over the period 1997-2012 indicates that (i) China's energy productivity growth may be overestimated if energy consumption structure is omitted; (ii) in regard to the contribution of specific energy input towards energy productivity growth, oil and electricity show positive contributions, but coal and natural gas show negative contributions; (iii) energy-specific productivity changes are mainly caused by technical changes rather than efficiency changes; (iv) the Porter Hypothesis is partially supported in China that carbon emissions control regulations may lead to energy productivity growth.

Keywords: Carbon emissions; Data envelopment analysis; Driving force; Input specific productivity indicator

1 Introduction

China attracts global attention not only for its rapid economic growth but also for its rapid increases in energy consumption and carbon emissions. China has been the world's second largest economy since 2013 (World Bank, 2014) and the largest energy-consuming country since 2011 (EIA, 2014). In addition, China has been responsible for the highest carbon emissions from fuel combustion (CDIAC, 2013), accounting for more than 20% of global CO_2 emissions since 2007. One of the goals of China's strategy for constructing a resource-saving and environmental friendly society and pursuing sustainable development is a reduction in carbon intensity (CO_2 emissions per GDP) by 40-45% by 2020 compared to the nation's 2005 level. Because the primary aim of social and economic development policy in China continues to be the maintenance of economic growth, to reduce its growth rates of carbon emissions requires an increase in both resource (especially energy) utilization

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efficiency and environmental efficiency. Another goal of China's sustainable development is the increase in energy efficiency defined as a reduction in energy intensity (energy consumption per GDP) by 32% by 2015 compared to the nation's 2005 level (SCC, 2007, 2011). This reduction also indicates an increase in energy efficiency. In addition, energy efficiency is a key indicator for issues on energy security maintenance and climate change mitigation.

Total factor energy efficiency is a widely used concept for energy efficiency measurement (e.g., Hu and Wang, 2006; Zhou and Ang, 2008; Wang H. et al., 2013; Wang K. et al., 2014). It is defined as the ratio between optimized energy input and actual energy input under a total factor framework in which the inputs of labor, capital stock, energy consumption, and other resources, as well as GDP output, are all taken into consideration. Furthermore, the concepts of environmental energy efficiency or ecological energy efficiency, as the extension of total factor energy efficiency, were proposed, in which the environmental factors such as air pollutants and carbon emissions from the combustion of fossil energy were taken into account (e.g., Zhang C. et al., 2011; Sueyoshi and Goto, 2011, 2012a; Wang Q. et al., 2012; Wang K. 2013b, 2013c; Zhang N. et al., 2014; Yang and Yang, 2015). These studies have defined energy and environmental efficiency as the ratio between environmental impact added (undesirable output) plus economic value added (desirable output) and energy consumed.

Energy and environmental efficiency is closely related to sustainability and is one of the indicators of the performance of energy utilization, economic development, and environmental protection under the notion of sustainable development (Mahlberg and Luptacik, 2014). It aims at achieving more economic outputs, consuming fewer resources (especially energy input), and producing fewer pollutant emissions. Therefore, measuring the energy and environmental efficiency of China is important to understanding the status and trends of energy consumption, economic growth, and environmental regulation; identifying the efficiency benchmark and efficiency-influencing factors; and ascertaining efficiency improvement areas and potentials. It makes sustainability accountable and helps to formulate policies and prioritize actions in China for economic growth, energy conservation, and carbon emissions control. Furthermore, in this study, we take CO_2 emissions into consideration when calculating energy and environmental efficiency, which serve to benchmark energy performance and assess its potential for CO_2 emissions reduction (Zhou et al., 2012). In addition, because China's sustainable development strategies and policies are proposed in the goals and regulations of both energy conservation and emissions reduction, and the realization of emissions reduction can be derived not only from energy saving but also from energy utilization efficiency promotion, energy consumption structure adjustment and optimization, as well as carbon capture and storage (CCS), etc., it is worthwhile to simultaneously evaluate China's energy and environmental efficiency to provide a more in-depth understanding of China's efforts on energy saving and emissions control.

In this study, we assume that decision making units (DMUs, the provinces in China) try to consume fewer inputs (energy) and minimize undesirable outputs (emissions) without affecting the desirable output (GDP). An efficiency analysis of the province requires a measurement of performance characterized by an energy and environmental efficiency frontier indicating efficient benchmarks related to the optimized objective of energy consumption and emissions. That is, provinces lying on the efficiency frontier are not able to reduce any energy input or emissions without reducing its economic outputs. These provinces are defined as efficient. A non-parametric method of data envelopment analysis (DEA) helps to identify such an efficiency frontier by defining efficiency as the ratio of a weighted sum of desirable outputs to a weighted sum of inputs; in addition, the weighted sum of undesirable outputs is also taken into consideration by specific technique (e.g. Färe et al., 1989; Färe and Grosskopf, 1996; Sahoo et al., 2011; Sueyoshi and Goto, 2012b; Wang K. et al., 2012; Mahlberg and Luptacik, 2014). DEA endogenously generates the most favorable weights[2] through linear programming optimization, which maximizes the desirable outputs or minimizes the inputs of a province under evaluation in comparison with the maximum attainable desirable outputs or the minimum attainable inputs.

The energy and environmental efficiency identified by a DEA model is purely a static efficiency measurement at a specific period that does not provide further information about energy and environmental efficiency change or production technology change over time. Chung et al. (1997) introduced a directional distance function model and, based on this model, proposed a productivity index that jointly models the productivity change of both desirable and undesirable outputs over time. In this study, we also try to extend the static energy and environmental efficiency analysis to an intertemporal energy and environmental productivity change analysis. The input-specific Malmquist productivity index (Färe et al. 1989, 1994; Caves et al., 1982) and the input-specific Luenberger productivity indicator (Chambers et al., 1996) are two indicators that are commonly used to calculate productivity change and its components, e.g., change in efficiency and technical change. The input-specific Malmquist productivity index has a ratio structure, while the input-specific Luenberger productivity indicator has an additive structure. The input-specific Malmquist productivity index is typically associated with the Russell measure (Färe et al., 1982, 1985) or the enhanced Russell measure (Pastor et al., 1999) of inefficiency which is multiplicative by nature, and the input-specific Luenberger productivity indicator is related to slack-based measure of efficiency in the directional distance function (Färe and Grosskopf, 2010) or the directional Russell measure of inefficiency (Fukuyama and Weber, 2009), which is additive by nature.

For a decomposition of the productivity index, on one hand, Färe et al. (1992) derived a Malmquist index based on an input-oriented model for measuring productivity change and disaggregated it into sub-indicators measuring changes in efficiency and technology. Based on an output-oriented model, Färe et al. (1994) later provided an alternative decomposition for identifying changes in efficiency, scale and technology. Simar and Wilson (1998) additionally decomposed the Malmquist index into four factors: changes in pure efficiency, scale efficiency, pure technology and scale of technology. This latter decomposition was also implemented inter alia by Wheelock and Wilson (1999) and Zofio (2007). On the other hand, Chambers et al. (1996) and Färe et al. (2008) decomposed the Luenberger productivity indicator into its efficiency change and technical change components. This measure is constructed from the directional distance functions which could adjust inputs and outputs simultaneously. Thus, in this study, we take the Luenberger productivity indicator to measure and decompose China's energy and environmental productivity change. In addition, inspired by the decomposition of the Malmquist index in Simar and Wilson (1998), this study decomposes the Luenberger energy and environmental productivity indicator into four factors that identify pure efficiency change, scale efficiency change, pure technology change, and change on the scale of technology in China. According to Zofio (2007), this four-factor

[2] A set of weights determined by linear programming that is optimal in the sense that it results in the best efficiency measure for the particular DMU under evaluation (Liang et al., 2008).

decomposition is a comprehensive decomposition that relies on generally accepted definitions of productivity change as well as technological and efficiency change from both technical and scale perspectives, thereby avoiding the scale bias of technical change.

As noted by Mahlberg and Luptacik (2014), Chang et al. (2012), Mahlberg and Shaoo (2011), and Wang C. (2011), different inputs play different roles in the production process[3], and a Malmquist index or Luenberger indicator associated with radial efficiency measures is not capable of attributing energy and environmental productivity change to changes in the utilization of specific energy inputs or the production of specific undesirable outputs. To overcome this limitation, this study develops, following the input-specific productivity change measures of Kapelko et al. (2015) and Mahlberg and Shaoo (2011), a Luenberger energy and environmental productivity indicator, which are shown as an aggregation of individual energy-specific productivity indicators and specific undesirable output productivity indicators. These decompositions enable us to examine the contributions of each individual energy input and undesirable output towards productivity change and its four components. Although Wang C. (2007) and Wang C. (2013) have also provided novel study frameworks to decompose energy productivity change into several components as efficiency and technical changes as well as changes in the capital-energy ratio, labor-energy ratio, energy supply structure and output structure[4], our decomposition provides a different perspective for understanding which specific energy inputs are the driving forces of energy productivity change.

The current study also differs from that of Kapelko et al. (2015), which provides a decomposition of input-specific productivity growth, yet only accounts for three factors (i.e., efficiency change, technical change under variable returns to scale, and scale efficiency change) and does not consider undesirable outputs. The current study is also different from those of Mahlberg and Shaoo (2011) and Mahlberg and Luptacik (2014), which measure input-specific eco-efficiency and eco-productivity change with the consideration of undesirable outputs while decomposing eco-productivity change into the two factors of efficiency change and technical change. Similar two-component decomposition can also be found in Yang and Yang (2015)'s energy and environmental productivity evaluation[5], Wu et al. (2012)'s energy productivity evaluation (with the constraints of carbon emissions), Chen et al. (2014)'s industrial total factor productivity evaluation[6], and Zhang and Ye (2015)'s environmental total factor productivity evaluation. Furthermore, our study goes one step

[3] In other words, the contributions of individual production factors to efficiency and productivity changes are different. For instance, for the energy consumption China in 2012, raw coal is mainly (70%) utilized for generating secondary energy such as thermal electricity, heating power and coke; oil (including gasoline, kerosene and diesel oil etc.) is mainly (60%) consumed in the transportation sector; while natural gas is almost equally consumed in industrial sector (36%) and residential sector. Moreover, when taking carbon emissions from fossil fuel into account, the contributions of individual energy inputs are also quite different for their carbon emissions factors are varied (Liu et al., 2015).

[4] These studies examine the contributions of technical progress as well as the changes in ratios of non-energy input over energy input to energy productivity change or energy intensity change of both OECD and non-OECD countries.

[5] Energy input, GDP desirable output and SO_2 undesirable output are utilized for estimation, while the effect of energy consumption structure is omitted in this study.

[6] One shortage of this study is that the homogeneity of DMU is likely to be violated because different industrial sectors are operating in different markets, facing different technologies, and using different input factors.

further than the decomposition of Simar and Wilson (1998), Wheelock and Wilson (1999) and Zofio (2007) in regard to the Malmquist index associated with the Shephard efficiency measure, as we provide an energy input-specific and undesirable output-specific Luenberger productivity change measurement and its decomposition in association with the directional Russell measure of inefficiencies.

In this study, the Luenberger energy and environmental productivity indicators and decomposition are further applied to an empirical analysis of energy and environmental productivity change in China during the period 1997-2012. The results of this analysis allow us to infer which energy inputs and/or emission outputs are the driving forces of productivity change, and which of the four aforementioned factors is the primary contributor of productivity change. To the best of our knowledge, this study provides the first attempt to analyze energy input-specific and environmental productivity change in China. The remainder of this paper is structured as follows. Section 2 presents the DEA based models and Luenberger indicators in detail. Section 3 describes the data. Section 4 reports and discusses the results of our empirical analysis. Section 5 concludes this paper.

2 Methodology

2.1 Energy and environmental inefficiency measurement

Under the total factor efficiency evaluation framework, a province could employ energy (e) and other resources (x) such as capital and labor as inputs to generate gross domestic product (g) as the desirable output; thus the production technology set can be defined as $T = \{(e, x, g)$: (e, x) can produce $(g)\}$, where T is a closed set and inputs and desirable outputs are assumed to be strongly disposable. Suppose that there are $j=1,2,\ldots,n$ provinces, and the input and output set of the jth province at period t is defined as $(e_{hj}^t, x_{ij}^t, g_{rj}^t)$, implying that there are $h=1,\ldots,k$ energy inputs, $i=1,\ldots,m$ non-energy inputs, and $r=1,\ldots,s$ desirable outputs. Then, adapting a slacks-based measure of inefficiency in the directional distance function context, the integrated energy inefficiency for each province at period t can be obtained by solving the following Model (1), in which the directional energy input distance function $D(E)^t$ seeks to reduce the consumption of energy input e_h^t at period t.

$$
\begin{aligned}
& D(E)_{V(C)}^t = \max \beta \\
& s.t. \ \sum_{j=1}^n \lambda_j e_{hj}^t \le e_{hj_0}^t - \beta d_h \qquad h=1,\ldots,k \\
& \qquad \sum_{j=1}^n \lambda_j x_{ij}^t \le x_{ij_0}^t \qquad i=1,\ldots,m \\
& \qquad \sum_{j=1}^n \lambda_j g_{rj}^t \ge g_{rj_0}^t \qquad r=1,\ldots,s \\
& \qquad \sum_{j=1}^n \lambda_j = 1 \\
& \qquad \lambda_j \ge 0 \qquad j=1,\ldots,n
\end{aligned}
\tag{1}
$$

In Model (1), β is a unified energy inefficiency measure for all types of energy inputs, d_h represents the direction in which energy input e_h^t can be scaled, and λ_j is the intensity variable that connects inputs and outputs by a convex combination. β=0 and β>0 indicate efficient and inefficient in energy utilization, respectively. Note that Model (1) is based on constant returns to scale (CRS) if the fourth constraint is omitted, or variable returns to scale (VRS) if it is functional. Thus, $D(E)_C^t$ and $D(E)_V^t$ denote the integrated energy inefficiency measure exhibiting CRS and VRS, respectively.

The energy inefficiency measured by Model (1) is considered to be an integrated/aggregative inefficiency measure which does not reflect the inefficiency of a specific energy resource in the production process. Thus the energy inefficiency measures obtained from it may lack insights if one wants to investigate the different impact and contribution of a specific energy resource among all input factors. To solve this shortage of not providing specific energy inefficiency measures, we propose the following Model (2), in which each kind of energy resource is assigned with a specific inefficiency measure β^h, $h=1,\ldots,k$, and $D(SE)^t$ is a Russell type of measure (Pastor et al., 1999; Fukuyama and Weber, 2009) in the directional energy input distance function context that sums together all of the specific energy inefficiencies.

$$
\begin{aligned}
& D(SE)_{V(C)}^t = \max \sum_{h=1}^{k} w^h \beta^h \\
& s.t. \ \sum_{j=1}^{n} \lambda_j e_{hj}^t \le e_{hj_0}^t - \beta^h d_h \qquad h=1,\ldots,k \\
& \quad \sum_{j=1}^{n} \lambda_j x_{ij}^t \le x_{ij_0}^t \qquad i=1,\ldots,m \\
& \quad \sum_{j=1}^{n} \lambda_j g_{rj}^t \ge g_{rj_0}^t \qquad r=1,\ldots,s \\
& \quad \sum_{j=1}^{n} \lambda_j = 1 \\
& \quad \lambda_j \ge 0 \qquad j=1,\ldots,n
\end{aligned}
\tag{2}
$$

In Model (2), d_h also represents the direction in which energy input e_h^t can be scaled. w^h is the normalized user specified weight associated with each type of energy input. $D(SE)^t$ is known as the aggregated specific energy inefficiency measure at period t, and its component β^h is considered to be the specific energy inefficiency measure. Model (2) is based on CRS if the fourth constraint is omitted, or VRS if it is functional. Thus, $D(SE)_C^t$ and $D(SE)_V^t$ respectively denote the aggregated specific energy inefficiency measure exhibiting CRS and VRS.

A limitation of the above Models (1) and (2) is that they do not include pollutant emissions caused by the consumption of energy when measuring the energy inefficiency. If we consider a production process in which each province employs energy (e) and non-energy (x) inputs to generate not only desirable output (g) but CO_2 emissions as undesirable output (b), then the production technology set will be modified as $T' = \{(e, x, g, b)\text{: } (e, x) \text{ can produce } (g, b)\}$. To reasonably model production technology that generates both desirable and undesirable outputs, we impose joint weak disposability and null-jointness assumptions (Färe et al., 1989) on the production technology set, implying that a proportional reduction in both desirable and undesirable outputs is necessary; and to produce desirable outputs some undesirable outputs must be produced. An aggregated specific energy inefficiency with the consideration of undesirable outputs, i.e., energy and environmental inefficiency, for each province at period t can then be obtained by solving the following Model (3), in which $D(EE)^t$ is a directional Russell measure combining the inefficiencies of both specific energy inputs and specific undesirable outputs. This directional distance function seeks to remove all slack in energy inputs and emission outputs.

$$
\begin{aligned}
& D(EE)_{V(C)}^{t} = \max\left(w^{E}\sum_{h=1}^{k} w^{h}\beta^{h} + w^{B}\sum_{f=1}^{l} w^{f}\beta^{f}\right) \\
& s.t.\ \sum_{j=1}^{n}\lambda_j e_{hj}^{t} \le e_{hj_0}^{t} - \beta^{h} d_h \qquad h=1,\dots,k \\
& \qquad \sum_{j=1}^{n}\lambda_j x_{ij}^{t} \le x_{ij_0}^{t} \qquad i=1,\dots,m \\
& \qquad \sum_{j=1}^{n}\theta_j\lambda_j g_{rj}^{t} \ge g_{rj_0}^{t} \qquad r=1,\dots,s \\
& \qquad \sum_{j=1}^{n}\theta_j\lambda_j b_{fj}^{t} = b_{fj_0}^{t} - \beta^{f} d_f \qquad f=1,\dots,l \\
& \qquad \sum_{j=1}^{n}\lambda_j = 1 \\
& \qquad \lambda_j \ge 0, 0 \le \theta_j \le 1 \qquad j=1,\dots,n
\end{aligned} \tag{3}
$$

In Model (3), there are f=1,…,l weakly disposable undesirable outputs. β^h is the specific energy inefficiency measure, and β^f is the specific emission or environmental inefficiency measure. d_h and d_f respectively indicates the direction in which energy input e_h^t and emission output b_f^t can be scaled. w^h and w^f are, respectively, the normalized user specified weight associated with each energy input and each emission output; w^E and w^B are the normalized user specified weights associated with energy inefficiency and environmental inefficiency measures, respectively.

As discussed by Färe et al. (1986), Färe and Grosskopf (2003, 2009), Kuosmanen (2005), and Kuosmanen and Podinovski (2009), a DEA model that satisfies VRS, output directional distance function, and weak disposability should be formulated as in Model (3), utilizing the abatement factor θ_j, which maintains the proportionality of reductions in desirable and undesirable outputs. Model (3) can be simply linearized as follows. First, we alter the variables to be $\theta_j\lambda_j = \lambda_j^1$ and set $(1-\theta_j)\lambda_j = \lambda_j^2$; then we have $\lambda_j = \lambda_j^1 + \lambda_j^2$. Using this linearization, Model (3) can be rewritten as Model (4).

$$
\begin{aligned}
& D(EE)_{V}^{t} = \max\left(w^{E}\sum_{h=1}^{k} w^{h}\beta^{h} + w^{B}\sum_{f=1}^{l} w^{f}\beta^{f}\right) \\
& s.t.\ \sum_{j=1}^{n}(\lambda_j^1+\lambda_j^2) e_{hj}^{t} \le e_{hj_0}^{t} - \beta^{h} d_h \qquad h=1,\dots,k \\
& \qquad \sum_{j=1}^{n}(\lambda_j^1+\lambda_j^2) x_{ij}^{t} \le x_{ij_0}^{t} \qquad i=1,\dots,m \\
& \qquad \sum_{j=1}^{n}\lambda_j^1 g_{rj}^{t} \ge g_{rj_0}^{t} \qquad r=1,\dots,s \\
& \qquad \sum_{j=1}^{n}\lambda_j^1 b_{fj}^{t} = b_{fj_0}^{t} - \beta^{f} d_f \qquad f=1,\dots,l \\
& \qquad \sum_{j=1}^{n}(\lambda_j^1+\lambda_j^2) = 1 \\
& \qquad \lambda_j^1, \lambda_j^2 \ge 0 \qquad j=1,\dots,n
\end{aligned} \tag{4}
$$

Model (4) is a linear programming model in terms of the optimization variables λ_j^1 and λ_j^2. $D(EE)_V^t$ represents the combined energy and environmental inefficiency exhibiting VRS. If we allow for CRS rather than VRS, θ_j is unnecessary. In that case, we return to Model (3) but omit the constraint $\sum_{j=1}^{n}\lambda_j=1$, remove θ_j, and obtain the optimal value, $D(EE)_C^t$, which represents the combined energy and environmental inefficiency exhibiting CRS.

Also noteworthy is the imposition of a strict equality constraint, as in the fourth constraint of Models (3) and (4), on undesirable outputs (Picazo-Tadeoa and Prior, 2009; Färe and Grosskopf, 2010; Zhou et al., 2012; Färe et al., 2014), which may have the disadvantage of allowing a downward-sloping portion of the efficiency frontier. To overcome this problem, Aparicio et al. (2013) proposed a nested environmental technology which establishes the production possibility set of period t as a subset of period t+1. In this study, we follow this approach to properly measure the shift in technology.

2.2 Energy and environmental productivity change measurement and decomposition

Next, we define the Luenberger productivity (LP) indicator as in Equation (5), in which "$D(\cdot)$" represents the various inefficiency measures of $D(E)$, $D(SE)$, or $D(EE)$ from Models (1) to (4).

$$\begin{aligned}LP(\cdot)_{t_1}^{t_2}=\frac{1}{2}\Big\{&\Big[D(\cdot)_C^{t_1}\left(e^{t_1},x^{t_1},g^{t_1},b^{t_1}\right)-D(\cdot)_C^{t_1}\left(e^{t_2},x^{t_2},g^{t_2},b^{t_2}\right)\Big]+\\&\Big[D(\cdot)_C^{t_2}\left(e^{t_1},x^{t_1},g^{t_1},b^{t_1}\right)-D(\cdot)_C^{t_2}\left(e^{t_2},x^{t_2},g^{t_2},b^{t_2}\right)\Big]\Big\}\end{aligned}\tag{5}$$

LP can be interpreted as an indicator of productivity change of province j from period t_1 to subsequent period t_2. Values of LP greater than, less than, or equal to 0, respectively indicates increase, decrease, or no change in productivity. LP indicator can be further decomposed into sub-indicators which respectively measures Luenberger pure efficiency change ($LPEC$), scale efficiency change ($LSEC$), pure change in technology ($LPTC$) and change in returns to scale of technology ($LTSC$) as in Equations (6) to (10).

$$LP(\cdot)_{t_1}^{t_2}=LPEC(\cdot)_{t_1}^{t_2}+LSEC(\cdot)_{t_1}^{t_2}+LPTC(\cdot)_{t_1}^{t_2}+LTSC(\cdot)_{t_1}^{t_2}\tag{6}$$

$$LPEC(\cdot)_{t_1}^{t_2}=D(\cdot)_V^{t_1}\left(e^{t_1},x^{t_1},g^{t_1},b^{t_1}\right)-D(\cdot)_V^{t_2}\left(e^{t_2},x^{t_2},g^{t_2},b^{t_2}\right)\tag{7}$$

$$\begin{aligned}LSEC(\cdot)_{t_1}^{t_2}=&\Big[D(\cdot)_C^{t_1}\left(e^{t_1},x^{t_1},g^{t_1},b^{t_1}\right)-D(\cdot)_V^{t_1}\left(e^{t_1},x^{t_1},g^{t_1},b^{t_1}\right)\Big]-\\&\Big[D(\cdot)_C^{t_2}\left(e^{t_2},x^{t_2},g^{t_2},b^{t_2}\right)-D(\cdot)_V^{t_2}\left(e^{t_2},x^{t_2},g^{t_2},b^{t_2}\right)\Big]\end{aligned}\tag{8}$$

$$\begin{aligned}LPTC(\cdot)_{t_1}^{t_2}=\frac{1}{2}\Big\{&\Big[D(\cdot)_V^{t_2}\left(e^{t_1},x^{t_1},g^{t_1},b^{t_1}\right)-D(\cdot)_V^{t_1}\left(e^{t_1},x^{t_1},g^{t_1},b^{t_1}\right)\Big]+\\&\Big[D(\cdot)_V^{t_2}\left(e^{t_2},x^{t_2},g^{t_2},b^{t_2}\right)-D(\cdot)_V^{t_1}\left(e^{t_2},x^{t_2},g^{t_2},b^{t_2}\right)\Big]\Big\}\end{aligned}\tag{9}$$

$$\begin{aligned}LTSC(\cdot)_{t_1}^{t_2}=\frac{1}{2}\Big\{&\Big[\Big(D(\cdot)_C^{t_2}(e^{t_1},x^{t_1},g^{t_1},b^{t_1})-D(\cdot)_V^{t_2}(e^{t_1},x^{t_1},g^{t_1},b^{t_1})\Big)-\\&\Big(D(\cdot)_C^{t_1}(e^{t_1},x^{t_1},g^{t_1},b^{t_1})-D(\cdot)_V^{t_1}(e^{t_1},x^{t_1},g^{t_1},b^{t_1})\Big)\Big]+\\&\Big[\Big(D(\cdot)_C^{t_2}(e^{t_2},x^{t_2},g^{t_2},b^{t_2})-D(\cdot)_V^{t_2}(e^{t_2},x^{t_2},g^{t_2},b^{t_2})\Big)-\\&\Big(D(\cdot)_C^{t_1}(e^{t_2},x^{t_2},g^{t_2},b^{t_2})-D(\cdot)_V^{t_1}(e^{t_2},x^{t_2},g^{t_2},b^{t_2})\Big)\Big]\Big\}\end{aligned}\tag{10}$$

$LPEC$ measures the change of contemporaneous pure efficiency at period t_1 and t_2. $LPEC$>0,

<0, or =0 indicate increase, decrease, or no change in pure technical efficiency. *LSEC* measures the change in scale efficiency resulted from the movement of province *j* in its input and output space over time or the change in the shape of technology, or a combination of the above two changes. *LSEC*>0, <0, or =0 indicate increase, decrease, or no change in scale efficiency. The calculation in the first and second sets of brackets in Equation (8) measures the difference between inefficiency scores under VRS and CRS at t_1 and t_2. *LPTC* measures the pure change in technology, defined as the arithmetic mean of the two differences which measure the shift of technology at t_1 and t_2. *LPTC*>0, <0, or =0 indicate technical progress (i.e., upward shift of technology), technical regress (i.e., downward shift of technology), or no change in technology. *LTSC* measures the change in returns to scale of technology at two fixed positions t_1 and t_2. *LTSC* is also an arithmetic mean of two differences, each of which measures the change in distance between inefficiency scores under VRS and CRS, where (e, x, g, b) remains constant. *LTSC*>0, <0, or =0 indicate that technology is moving toward CRS, moving opposite CRS, or undergoing no change.

We emphasize that $D(\cdot)^{t_1}_{V(C)}\left(e^{t_1}, x^{t_1}, g^{t_1}, b^{t_1}\right)$ and $D(\cdot)^{t_2}_{V(C)}\left(e^{t_2}, x^{t_2}, g^{t_2}, b^{t_2}\right)$ can be directly obtained by solving the above DEA models with contemporary data, while $D(\cdot)^{t_1}_{V(C)}\left(e^{t_2}, x^{t_2}, g^{t_2}, b^{t_2}\right)$ and $D(\cdot)^{t_2}_{V(C)}\left(e^{t_1}, x^{t_1}, g^{t_1}, b^{t_1}\right)$ can be obtained by solving these models with intertemporal data. To reduce infeasible solutions, when calculating the intertemporal inefficiency, a combined efficiency frontier of period t_1 and t_2 is applied instead of separately referring to the frontier of period t_1 or t_2[7].

Note that Luenberger productivity indicators calculated based on the integrated or aggregated inefficiency measures, $D(E)^t_{V(C)}$, $D(SE)^t_{V(C)}$, and $D(EE)^t_{V(C)}$, are not capable of attributing energy productivity change to changes in utilizing a specific energy resource. Therefore, we further use β^h, h=1,…,k, obtained from Model (2) to define $D(\beta^h)^t$, which is the inefficiency measure for the hth specific energy input at period t. Through utilizing $D(\beta^h)^t$, the Luenberger specific energy productivity indicators enable one to examine the contributions of individual energy input to integrated energy productivity change.

3 Data and descriptions

We utilize the Luenberger productivity indicator to measure and decompose the energy and environmental productivity change of China's 30 provincial-level regions over the period 1997- 2012, covering the later years of the 9th Five-Year Plan (FYP) period (1997-2000), the 10th and 11th FYP periods (2001-2005 and 2006-2010), and the beginning years of the 12th FYP period (2011-2012). The input variables of labor force, capital stock, and total energy consumption, as well as the desirable output variable of GDP and the undesirable output variable of CO_2 emissions, are utilized. Total energy consumption is further decomposed into four major energy consumptions: coal, oil, natural gas, and electricity, which are all final

[7] It should be noticed that, the combined efficiency frontier of t_1 and t_2 helps to eliminate infeasibilities only when the reference technology of t_2 (including observations from both t_1 and t_2) is utilized to evaluate observations from t_1, but it does not eliminate infeasibilities when the reference technology of t_1 (including observations from both t_1 and the period prior to t_1) is utilized to evaluate the observations from t_2. Thus, the combined efficiency frontier of t_1 and t_2 is just used for evaluating the observations from t_1, and the efficiency frontier of t_1 is used for evaluating the observations from t_2.

consumption[8]. Labor force and GDP data are obtained from the China Statistical Yearbooks. Capital stock data are obtained from Shan (2008) and our estimation (Wang et al., 2012; Wang et al., 2013a). Data on total energy consumption and specific energy consumptions are collected from the China Energy Statistical Yearbook. We estimate CO_2 emissions based on fossil fuel consumption, conversion factors from physical unit to coal equivalent (NBS, 2013) and carbon emissions factors for fossil fuel combustion provided in IPCC (2006). We first disaggregate the fossil fuel consumption into sub-item fossil fuel consumptions[9] according to China's provincial energy balance pivot tables. These sub-item fossil fuel consumptions are then converted into calorific value according to the conversion factors. Third, the sub-item fossil fuel consumption-based calorific values of China's provinces are further translated into its CO_2 emissions. Thus, data on CO_2 emissions are neither directly tied to total energy consumption nor directly proportional to the specific energy inputs of coal, oil, or natural gas. Monetary data on GDP and capital stock are converted into 2010 constant prices, and data on energy consumptions are converted into tonnes of coal equivalent (tce) according to the conversion factors. Table 1 summarizes the descriptive statistics of the input and output data for selected years.

[Insert Table 1 here]

Table 1 shows that China's total energy consumption increased significantly over the period 1997-2012, in which an increase in natural gas was most obvious, followed by an increase in electricity. However, the proportions of natural gas consumption and electricity consumption during the entire study period were relatively low compared with the proportion of coal consumption; thus clearly indicating the character of China's energy resource endowment: rich in coal, short of oil, and lacking in natural gas. It can be seen in Figure 1 that although the structure of final energy consumption had been promoted with the decreasing share of coal and increasing share of other relatively clearer energies, the promotion process was slow. Figure 2 shows that the ratio of GDP over energy consumption in China experienced a continuous increase during the periods 1997-2002 and 2006-2012; however, this increase was temporarily interrupted in 2003 and 2005. This indicates that China's GDP outputs grew faster than its energy input in general, but the improvement was not continuous. Based on these phenomena, we expect an overall increase in energy productivity for China over our study period, while the productivity changes over different FYP periods may vary.

[Insert Figures 1 and 2 here]

4 Empirical results

We calculate three types of productivity indicators that denote integrated energy productivity change, aggregated specific energy productivity change, and energy and environmental productivity change. Differences between the first and second indicators reveal the effect of energy consumption structure in energy productivity change analysis, while differences between the second and third indicator denote the effect of environmental concerns or

[8] Final energy consumption refers to the total energy consumption in the region in a given period but excludes the consumption in conversion of the primary energy (e.g., coal, oil, natural gas) into the secondary energy (electricity) and the loss in the process of energy conversion. Thus, the final energy consumptions (instead of total energy consumption) of coal, oil, natural gas, and electricity are used for calculation in this study so as to avoid double counting.

[9] Including the final consumption and the consumption in conversion (from primary energy into secondary energy) of raw coal, cleaned coal, other washed coal, briquettes, coke, coke oven gas, other gas, crude oil, gasoline, kerosene, diesel oil, fuel oil, liquefied petroleum gas, refinery gas, and natural gas.

environmental regulations on energy productivity analysis.

When measuring these productivity changes, calculations are undertaken between two consecutive years, and the directional vectors (d_h, d_f) utilized are the actual energy input (combined or specific) level and actual emission output level of each province at each year[10]. These directional vectors guarantee that the inefficiency measures of β^h and β^f are unit-invariant. As indicated in Briec and Kerstens (2009), the directional distance function based intertemporal inefficiency measures may yield infeasibilities[11]. The same problem occurs in our calculation accounting for an approximate 7% of the initial example of intertemporal inefficiency measures. We remove these infeasibilities from the calculation of the mean values of productivity indicators.

It should be noted that due to interprovincial energy trade and commuting, our observations in this study are not absolutely economically independent, i.e., provinces may influence each other through neighborhood effects (Anselin, 1988; LeSage and Pace, 2009; Burnett et al., 2013). In the case of DEA application, if observations are not independent, the inefficiency estimation may be biased if viewed from a long-term performance point of view. To reduce the estimation bias, we divide the study period into four periods which contain 2 to 5 years of observations according to data availability, and calculate the productivity indicators in each period individually. The length of each study period herein is shorter than that used in Mahlberg and Shaoo (2011) and Zhang C. et al. (2011). Although this may not completely eliminate the possible estimation bias caused by neighborhood effects, it helps to alleviate such bias through short-term estimation.

4.1 Integrated energy productivity change

The integrated energy productivity indicator in China and its decomposition are reported in the second to the sixth rows of Table 2. It can be seen that China's integrated energy productivity change is positive (1.77%) on average over the period 1997-2012, yet this growth is inconsistent. The latter four years of the 9th FYP period and the beginning two years of the 12th FYP period show the most significant productivity growth (4.48% and 2.01%); however, productivity change is negligible in the 10th FYP period (0.02%).

[Insert Table 2 here]

The data in columns 4 to 7 of Table 2 present the contributions to integrated energy productivity change from pure efficiency change, scale efficiency change, pure change in technology, and change in returns to scale of technology. For the entire study period, pure change in technology and change in returns to scale of technology play positive roles, but pure efficiency change and scale efficiency change play negative roles. For the four FYP periods, it is obvious in Figure 3 that pure change in technology and change in returns to scale of technology are always major driving forces for integrated energy productivity growth. There is only one exception that pure change in technology plays a negative role in the 10th FYP period. Figure 3 further shows that pure efficiency decreases during the periods

10 For the discussions and comparisons of using a directional distance function with different directional vectors, see Färe er al. (2007) for a nonparametric DEA example, or Vardanyan and Noh (2006) for a parametric example. It should be clarified that the different directional vectors chosen can generate rather different estimates of inefficiencies both for nonparametric and parametric models and that no single estimation is superior to all others (Lee, 2015).

11 Infeasibility is not specific to the Luengerber productivity indicator (or Malmquist index) and may be logically unavoidable under certain specifications of data structure, technology, and the choice of directional vector. Briec and Kerstens (2009) recommend simply reporting any infeasibility that occurs in the empirical analysis.

2001-2005 and 2011-2012, and scale efficiency decreases during the periods 2006-2010 and 2011-2012, both of which slow down integrated energy productivity growth. These findings indicate that over the entire study period, there exists an upward shift in energy technology in China and that this technical progress is the most important contributor for integrated energy productivity growth. However, contemporaneous pure technical efficiency decrease slows down China's integrated energy productivity growth.

[Insert Figure 3 here]

4.2 Aggregated specific energy productivity change

In this section, the productivity changes of specific energy inputs and aggregated specific energy productivity change are calculated. The normalized weight w^h associated with each specific energy input in Model (2) is equalized (1/4) to avoid the effect of large degrees of difference on the magnitude of the consumption values of these four specific energy inputs. Similar treatment is utilized in the modeling of Kapelko et al. (2015) and Mahlberg and Shaoo (2011). The calculated results can be found in Table 2 and in Figure 4.

[Insert Figure 4 here]

When energy consumption structure is taken into consideration, the energy productivity growth becomes negative in the 10th FYP period and becomes lower in the other three FYP periods compared with integrated energy productivity growth in corresponding periods. For the entire study period, the aggregated specific energy productivity growth is lower than the integrated energy productivity growth, which is mainly denoted by an obvious shift in pure technology change from growth (1.01%) to decline (-1.66%). As we mentioned above, the present status of China in regard to resource endowment is rich in coal, short of oil, and lacking in natural gas, and compared with oil and natural gas, the utilization of coal is comparatively lower in efficiency and higher in carbon emissions in combustion processes. During our study period, on one hand, the percentage of coal consumption in the total final energy consumption decreased by 14%, and by 2012, this percentage was still as high as approximately 50%. On the other hand, the percentages of consumptions of oil and natural gas in the total final energy consumption increased by 2% and 3%, respectively, and by 2012, these resources together accounted for 27% of China's total final energy consumption. Therefore, although the dominance of coal consumption in total final energy consumption has gradually begun to change, the energy consumption structure has not fundamentally changed during the study period. The dominance of coal consumption and the slow and unobvious improvements in energy consumption structure may result in lower aggregated specific energy productivity growth than integrated energy productivity growth.

Next, we further analyze the contribution of the productivity change of each energy resource. It can be seen that (i) coal-specific productivity change is negative (-0.03%). Although its *LTSC* score is positive, indicating a positive change (2.18%) in returns to scale of technology, its *LPEC*, *LPTC*, and *LSEC* scores are all negative, indicating that for the utilization of coal, pure technical efficiency declines (-0.10%), pure technology regresses (-1.77%), and there is a negative change (-0.34%) in the shape of technology. (ii) Oil-specific productivity change is positive (2.43%), and productivity growth is due to increases in *LPTC* (1.54%), *LTSC* (0.91%), and *LPEC* (0.44%). (iii) Natural gas specific productivity change is negative (-0.69%). Although its *LPEC*, *LSEC* and *LTSC* scores are all positive, a significant pure technical regress (-6.11%) offsets these growth effects. (iv) Electricity-specific productivity change is positive (1.17%); this growth is mainly caused by increases in *LPEC* (0.38%) and

LTSC (1.11%).

Figure 5 illustrates the different contributions of *LPEC*, *LPTC*, *LSEC*, and *LTSC* to *LP* for each specific energy input over the entire study period. It is obvious that pure technical change is the largest driving force for both oil- and natural gas-specific productivity changes and is the second largest driving force for coal specific productivity change. We should note, however, that pure technical change plays a positive role in the growth of oil-specific productivity while reducing coal- and natural gas-specific productivities. Meanwhile, growth in returns to scale of technology is always the major driving force for growth on these four energy-specific productivities.

[Insert Figure 5 here]

It also can be seen in Figure 5 that for four energy-specific inputs, the joint effect of change on technology (pure technical change and change in returns to scale of technology) plays a more important role than the joint effect of efficiency change (pure technical efficiency change and scale efficiency change) in the growth of energy productivity. This outcome reveals that China's energy-specific productivity changes can be attributed to technical changes rather than efficiency changes. Namely, the shift in technology contributes more than the catch-up effect to China's aggregated specific energy productivity change.

The above results and analysis raise the question of which specific energy inputs are the primary causes of changes in *LP*, *LPEC*, *LPTC*, *LSEC*, and *LTSC*. Figure 6 answers this question by illustrating the contributions of four types of specific energy inputs to energy productivity change. In summary, aggregated specific energy productivity growth is mostly driven by the productivity growth of oil overall in China, and within the specific productivity growth of oil, technical progress is identified as the largest driving force.

[Insert Figure 6 here]

4.3 Energy and environmental productivity change

In this section, we absorb undesirable outputs (carbon emissions) into the measurement of productivity change to identify the role of emissions in energy productivity change. Models (3) and (4) are applied to measure aggregated specific energy efficiency with the consideration of undesirable outputs. Similarly, the weights w^h and w^f are equally assigned (1/5) because we have four specific energy inputs and one emission output. In addition, the normalized weights w^E and w^B are also equally assigned (1/2) because we consider that energy and environmental inefficiency measures have same importance in the estimation. The results are reported in the last five rows in Table 2 and illustrated in Figure 7.

[Insert Figure 7 here]

It can be seen that, over the entire study period, China's energy productivity growth may be slightly underestimated if undesirable outputs are ignored. However, this underestimation is not consistent in different FYP periods. It is underestimated in the last four years of the 9th FYP period and the 11th FYP period, but overestimated in the 10th FYP period and first two years of the 12th FYP period. Several previous studies found that developing countries usually have lower productivity growth when undesirable outputs are taken into consideration (e.g., Zhang C. et al., 2011; Kumar, 2006). Our findings in the current study partially agree with this argument in the specific period that China's energy productivity growth is underestimated if carbon emissions are ignored. However, it should be noted that our study specifically focuses on the identification of energy productivity change instead of total factor productivity change, as in previous studies. Furthermore, out results signify that different FYP periods exhibit different characteristics in regard to productivity change. For the periods 1997-2000, 2006-2010, and 2011-2012, energy and environmental productivity experiences continuous growth. However, during the 10th FYP period, it experiences a decrease process. For the entire study period, the average energy and environmental productivity change is 0.97%, indicating a moderate improvement in the performance of energy utilization and carbon emissions control.

Figure 8 further illustrates the differences between aggregated specific energy productivity change and energy and environmental productivity change through decomposed indicators. It is obvious that when ignoring undesirable outputs, *LPEC*, *LPTC* and *LSEC* may be underestimated but *LTSC* may be overestimated. This finding reveals that the role of undesirable output in energy productivity change varies. The consideration of CO_2 emissions from energy utilization plays a positive role in pure technical efficiency growth and scale efficiency change, as well as pure technical change, but makes a negative contribution to the change in returns to scale of technology. This result partially supports the Porter Hypothesis (Porter and van der Linde, 1995) from the perspective of changes in pure technical efficiency, scale efficiency, and pure technology that environmental regulations can lead to productivity growth.

[Insert Figure 8 here]

5 Conclusions

In this study, we sought to extend the literature on energy and environmental productivity analysis. Considering the argument that a government's decision-making process in regard to energy policy requires an assessment of the productivity change of individual energy inputs to provide insights into the scope for improvement of the utilization of specific energy inputs, we develop a Luenberger aggregated specific energy productivity indicator and an energy and environmental productivity indicator which account for the various impacts of specific energy inputs and emission outputs towards the measurement of productivity change. The aggregated specific energy productivity indicator is shown as a combination of the individual energy input specific productivity indicators, and the integrated energy and environmental productivity indicator is shown as the combination of energy productivity and environmental productivity indicators. Furthermore, these Luenberger indicators can be further seen as the composite measurement of four factors: pure efficiency change, scale efficiency change, pure technology change and scale of technology change which help to identify the catch-up effect, frontier shift effect and the economy of scale towards productivity growth. This approach is used to analyze China's energy and environmental productivity change over the period 1997-2012. The empirical results are as follows.

(i) When energy consumption structure is omitted, and without taking into account carbon emissions from fuel combustion, an average integrated energy productivity growth of 1.77% overall in China is observed in which the most significant growth is observed in the later years of the 9th Five-Year Plan period and the beginning years of the 12th Five-Year Plan period, yet the productivity change is negligible in the 10th FYP period.

(ii) When energy consumption structure is taken into consideration, an average aggregated specific energy productivity growth of 0.78% overall in China is identified, which is approximately 1% lower than the integrated energy productivity growth. The obvious shift in pure technical change from positive under integrated energy productivity indicator to negative under aggregated specific energy productivity indicator explains this reduced level of productivity growth. This finding revels that the adjustment on energy consumption structure in China during the study period is not very effective, and China is still suffering from the restriction of energy resources endowment that coal consumption dominates the total final energy consumption.

(iii) The measurement of specific energy input productivity change shows the contribution of each energy resource towards productivity change in China. First, oil and electricity inputs show positive contributions to aggregated specific energy productivity growth, but coal and natural gas inputs show negative contributions. Second, growth in returns to scale of technology is the largest driving force for both coal-specific and electricity-specific productivity growths; pure technical change is the largest driving force for both oil-specific productivity growth and natural gas specific productivity decline. Third, in general China's energy-specific productivity changes are caused primarily by technical changes rather than efficiency changes. Namely, a shift in technology contributes more than the catch-up effect to China's energy-specific productivity change.

(iv) China's energy productivity growth may be underestimated if CO_2 emissions are ignored. In particular, when ignoring CO_2 emissions, pure technical efficiency change, pure technology change, and scale efficiency change may be underestimated, but change in returns to scale of technology may be overestimated. This finding partially supports the Porter Hypothesis in China that environmental regulations can lead to productivity growth.

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Figures and Tables

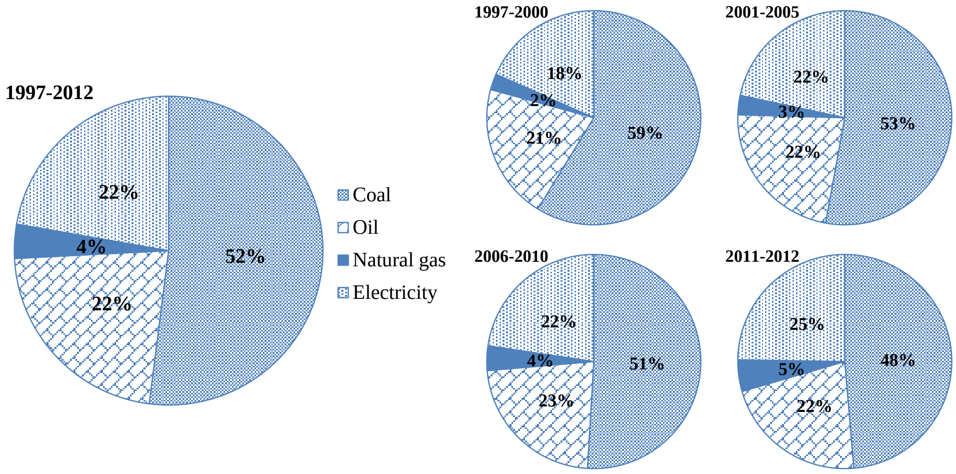

Figure 1 Distribution of specific final energy consumptions in total final energy consumption

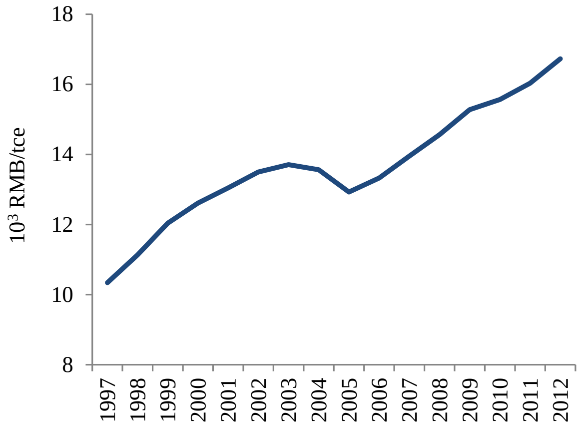

Figure 2 Ratio of GDP over final energy consumption

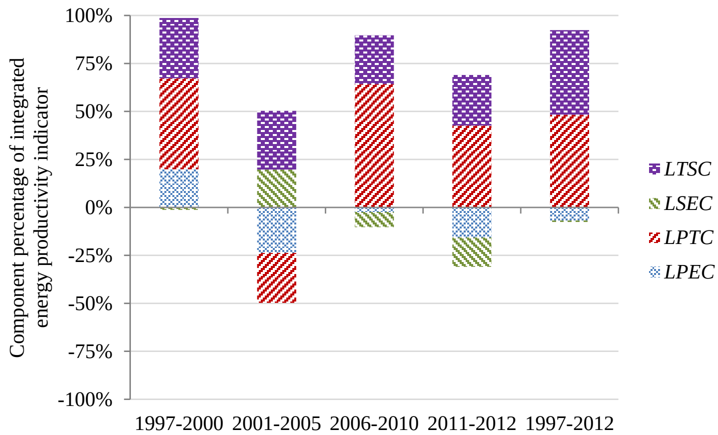

Figure 3 Integrated energy productivity change and it decomposition

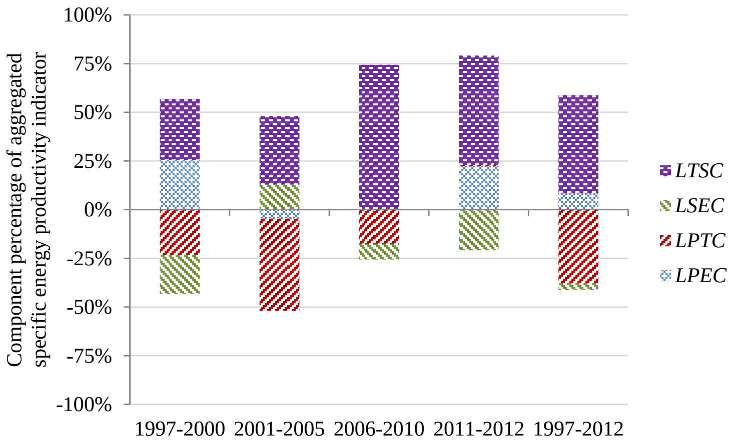

Figure 4 Aggregated specific energy productivity change and its decomposition

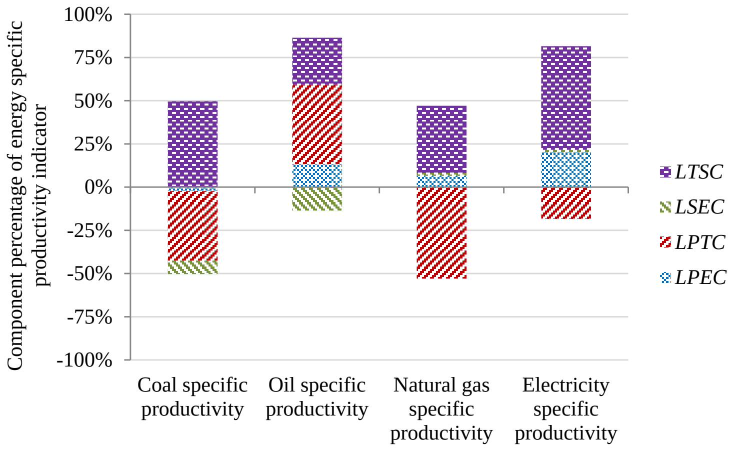

Figure 5 Contribution of *LPEC*, *LPTC*, *LSEC*, and *LTSC* to energy-specific productivity change

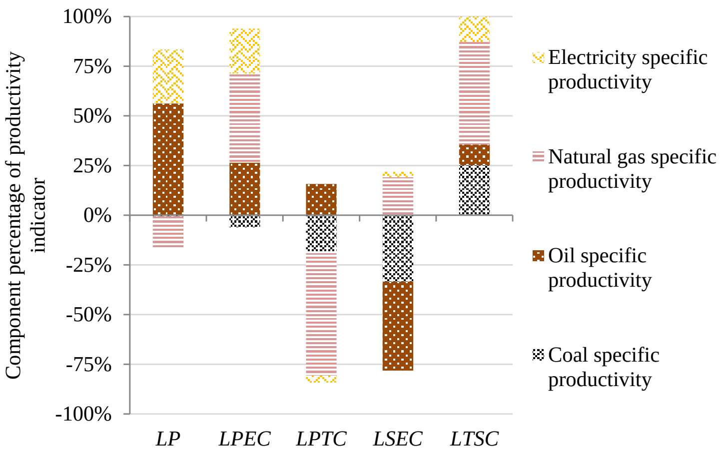

Figure 6 Contribution of energy-specific productivity change to aggregated specific energy

productivity change

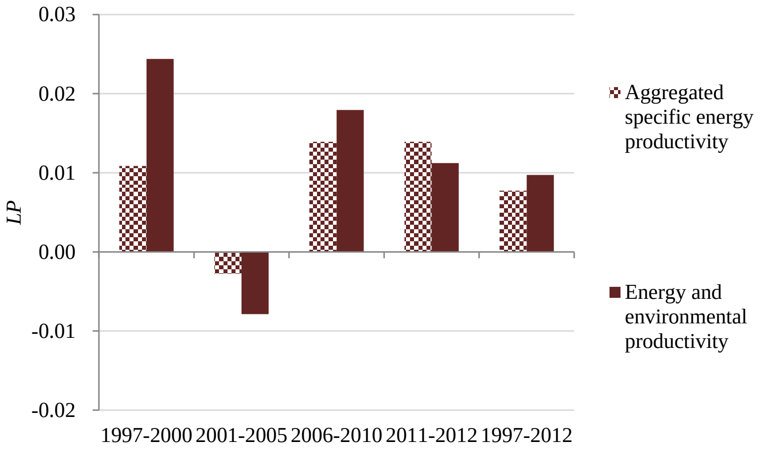

Figure 7 Comparison of two energy productivity indicators

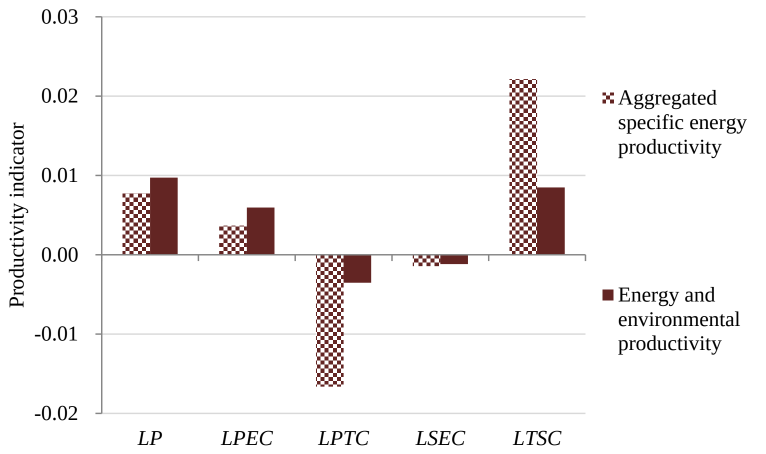

Figure 8 Comparison of two energy productivity indicators and their decomposed indicators

Table 1 Descriptive statistics of inputs and outputs

Inputs and outputs		Year	Total	Mean	Max	Min	Std. dev.
Desirable output	GDP (billion RMB)	1997	10292.92	343.10	1034.33	32.04	249.11
		2012	53825.01	1794.17	5476.47	172.13	1353.46
Non-energy inputs	Labor (thousand person)	1997	635464.00	21182.13	50170.00	2354.00	13856.29
		2012	765292.68	25509.76	60313.01	2936.03	16980.12
	Capital (billion RMB)	1997	16273.24	542.44	1515.85	63.74	381.84
		2012	135781.03	4526.03	12215.47	643.66	3015.93
Energy input	Total energy (million tce)	1997	995.33	33.18	67.54	2.86	17.94
		2012	3217.83	107.26	288.71	15.39	65.08
Specific energy inputs	Coal (million tce)	1997	614.73	20.49	49.64	0.46	11.40
		2012	1544.36	51.48	167.15	1.78	37.42
	Oil (million tce)	1997	192.38	6.41	24.90	0.27	5.53
		2012	715.28	23.84	76.75	2.72	18.59
	Natural gas (million tce)	1997	22.54	0.75	6.58	0.01	1.35
		2012	161.26	5.38	19.63	0.42	4.03
	Electricity (million tce)	1997	165.69	5.52	15.16	0.28	3.91
		2012	796.92	26.56	73.94	2.67	18.66
Undesirable output	CO_2 (million tonne)	1997	3068.66	102.29	223.93	6.69	59.00
		2012	9922.97	330.77	877.09	46.72	208.97

Table 2 Productivity indicators

Indicator	Period	*LP*	*LPEC*	*LPTC*	*LSEC*	*LTSC*
Integrated energy productivity change	1997-2000	0.0448	0.0091	0.0218	-0.0006	0.0144
	2001-2005	0.0002	-0.0059	-0.0064	0.0049	0.0076
	2006-2010	0.0180	-0.0005	0.0145	-0.0018	0.0058
	2011-2012	0.0201	-0.0083	0.0226	-0.0081	0.0140
	1997-2012	**0.0177**	**-0.0014**	**0.0101**	**-0.0002**	**0.0092**
Aggregated specific energy productivity change	1997-2000	0.0109	0.0201	-0.0182	-0.0157	0.0247
	2001-2005	-0.0028	-0.0032	-0.0340	0.0094	0.0251
	2006-2010	0.0139	0.0000	-0.0050	-0.0023	0.0212
	2011-2012	0.0139	0.0053	0.0002	-0.0050	0.0134
	1997-2012	**0.0078**	**0.0037**	**-0.0166**	**-0.0014**	**0.0221**
Coal specific productivity change	1997-2000	0.0397	0.0220	0.0110	-0.0202	0.0269
	2001-2005	-0.0055	-0.0117	-0.0388	0.0104	0.0346
	2006-2010	-0.0268	-0.0029	-0.0152	-0.0009	-0.0079
	2011-2012	0.0190	-0.0042	-0.0144	-0.0189	0.0566
	1997-2012	**-0.0003**	**-0.0010**	**-0.0177**	**-0.0034**	**0.0218**
Oil specific productivity change	1997-2000	0.0223	0.0149	-0.0043	-0.0147	0.0264
	2001-2005	-0.0100	0.0028	-0.0089	0.0117	-0.0156
	2006-2010	0.0536	0.0032	0.0360	-0.0130	0.0275
	2011-2012	0.0398	-0.0041	0.0539	-0.0087	-0.0013
	1997-201	**0.0243**	**0.0044**	**0.0154**	**-0.004**	**0.0091**

	2				**6**	
Natural gas specific productivity change	1997-2000	-0.0258	0.0239	-0.0554	-0.0194	0.0251
	2001-2005	-0.0084	-0.0025	-0.0808	0.0093	0.0656
	2006-2010	0.0135	0.0002	-0.0404	0.0047	0.0490
	2011-2012	-0.0258	0.0264	-0.0723	0.0086	0.0115
	1997-2012	**-0.0069**	**0.0075**	**-0.0611**	**0.0020**	**0.0448**
Electricity specific productivity change	1997-2000	-0.0001	0.0197	-0.0157	-0.0086	0.0045
	2001-2005	0.0086	-0.0015	-0.0144	0.0063	0.0182
	2006-2010	0.0176	-0.0003	0.0002	0.0000	0.0178
	2011-2012	0.0227	0.0032	0.0334	-0.0009	-0.0131
	1997-2012	**0.0117**	**0.0038**	**-0.0034**	**0.0003**	**0.0111**
Energy and environmental productivity change	1997-2000	0.0244	0.0221	0.0093	-0.0007	-0.0063
	2001-2005	-0.0079	0.0076	-0.0287	0.0013	0.0120
	2006-2010	0.0179	0.0010	0.0102	-0.0039	0.0107
	2011-2012	0.0112	-0.0099	0.0058	-0.0012	0.0165
	1997-2012	**0.0097**	**0.0059**	**-0.0035**	**-0.0012**	**0.0085**