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Carbon-weighted economic development performance and driving force analysis: Evidence from China

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ABSTRACT

Based on a data envelopment analysis framework, this study develops an indicator termed as carbon-weighted economic development (CWED) covering the dimensions of energy, environment, economy and resources to measure the economic development performance in a carbon-emission conscious economy. As an empirical application, the proposed approach is applied to a case study of 30 provinces in China. In addition, to identify the driving forces underlying low-carbon economic development in China, we analyze the endogenous interactions and dynamic behaviors between CWED, Foreign Direct Investment, foreign trade, industrial structure, local fiscal expenditure and energy consumption structure using a panel vector auto-regression model. The main findings show that, (1) adjusting industrial structure by vigorously developing the service industry and reducing the coal energy share in the primary energy consumption structure are the two most effective approaches to improve CWED in both the short-run and long-run; in return, CWED has positive feedback effects on both approaches in the long-run; (2) increase of the fiscal expenditure has a short-term positive effect on CWED; (3) FDI has an indirect negative effect on CWED in the long-run and foreign trade has an indirect positive effect on CWED in the short-term.

1. Introduction

The limitation of gross domestic product (GDP) as a measure of sustainable development for a country was first underlined at the United Nations Conference on Environment and Development in 1992. Since then, economic measures taking into account the effects of both GDP and other factors such as environmental protection to better reflect development quality have been discussed and proposed (Nourry, 2008). Environmental destruction brought by global warming, for instance, is one of the most challenging problems facing human race because it requires complex negotiations and collaborations among nations (Adger et al., 2013). How to curtail energy consumption and environmental pollution while maintaining growth rate of industrial productivity, in other words, promoting the development of a low-carbon economy, has become a top-priority issue to tackle for many countries. In fact, low-carbon economy is a sustainable long-term development regime encompassing many factors such as economy, society, environment, politics, law and culture (Dagoumas and Barker, 2010; Dou, 2013; Hu et al., 2011).

To design and implement suitable policies for overcoming the barriers in achieving a low-carbon economy, every country shall adopt a sound and balanced measure for economic development, which accounts for the benefits of low-carbon in place of the traditional measure that puts a dominating weight on the GDP growth factor. Development of low-carbon economy requires the fusion of multiple objectives arising from sustainable energy policy, environmental protection, economic growth, resource conservation, efficiency improvement and productivity growth. In this paper, we propose an index to measure the economic development in low-carbon system as “carbon-weighted economic development” (CWED), an indicator reflecting the cost-benefit of efforts that integrate economic growth, carbon emission and sequestration, energy consumption, and other resources needed in production.

While the importance of CWED is self evidently clear, it is surprising that there is neither well-developed definition, nor formal operational procedure on measuring the concept found in the literature. Regarding the theory and practice of CWED, several key fundamental questions need to be addressed, which are : (1) how to define CWED; (2) how to quantitatively measure it; (3) what economic factors significantly influence it. We address them through both theoretical analysis and

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empirical study of evidences from China.

To measure the development of low-carbon economy, multi-criteria decision analysis (MCDA) approaches are implemented to assess the trade-offs in a low-carbon economic system. In the realm of low-carbon or sustainable development, MCDA like goal programming (Jayaraman et al., 2015), risk management (Jackson, 2010) and portfolio decision analysis (Salo et al., 2011) are applied to evaluate different choices of strategic policies and investments balancing the rewards and risks.

Data envelopment analysis (DEA) is commonly used in calculating the relative efficiency among the assessed objectives in a low-carbon economic system from the input-output analysis perspective. Productivity has been widely recognized as a measure of economic prosperity, standard of living and the quality of an economy. There have been several studies investigating indicators related to low-carbon economic development. The Malmquist productivity (MP) indicator is one such example (Malmquist, 1953) which is usually obtained by measuring the efficiency of decision-making units (DMUs) under the framework of traditional radial DEA. Regional analysis of total factor energy efficiency in China and Japan is performed in (Chang and Hu, 2010a, 2010b; Honma and Hu, 2009; Hu and Wang, 2006).

MP represents total factor productivity (TFP) growth, reflecting changes in both technical efficiency and frontier technology of a DMU between two periods. However, in many circumstances, especially when analyzing low-carbon economy, undesirable side-product (for instance, CO_2 emissions) may be produced along with the desirable outputs. Malmquist-Luenberger productivity (MLP) index, first proposed in Chambers et al. (1996), is subsequently applied in the area of environmental and energy studies by Chung et al. (1997). MLP is based on measuring inefficiency of DMUs using directional distance function (DDF) to accommodate undesirable outputs (see Emrouznejad and Yang, 2016a, 2016b; Wang et al., 2015; Yao et al., 2015). Nonetheless, the DDF method is susceptible while there are slacks in the technological constraints, which would lead to underestimation of the inefficiency. Accounting for this issue, Fukuyama and Weber (2009) improve the DDF method to get a directional slacks-based measure of technical inefficiency (DSBI) which generalizes some of the existing slacks-based measures of inefficiency.

We contribute to the literature by proposing a CWED index that better measures the low-carbon economic development. We establish a quantitative approach to measure CWED under the framework of MLP index through measuring inefficiency by a modified DSBI including non-conventional inputs and undesirable outputs. Through defining and measuring CWED index, we provide a tool for policy makers to evaluate the low-carbon economic development. We extend theories and empirical methods of previous researches on analyzing the driving forces behind low-carbon economic development through endogenous growth models using panel vector auto-regression (PVAR). We are also able to formulate five testable hypotheses regarding the relationships between the CWED driving factors and the low-carbon economic growth and then test them with empirical data. Practical insights and policy implications for policy makers are drawn from the empirical study using the data of China from 1998 to 2014.

With CWED defined, the driving forces behind low-carbon economy development need to be explored to find effective ways to improve CWED. Existing research using the index dividing methods (Chang and Hu, 2010a, 2010b; Emrouznejad and Yang, 2016a, 2016b) or the econometric tools (Fisher-Vanden et al., 2006) to identify the driving factors either neglect some relevant economic variables that are not directly used in the index measuring process or overlook the endogeneity between these economic variables. Moreover, the feedback effect of low-carbon economic development on the driving forces is ignored.

Many economic factors may drive the low carbon economic development in short or long-run. First of all, the four main driving factors in traditional economic growth literature are considered: FDI (Borensztein et al., 1998; Chang, 2010; Mehic et al., 2013), foreign trade (Badinger, 2005; Dollar, 1992; Edwards, 1998), industrial structure (Lande, 1994; Shaffer, 2009) and local fiscal expenditure (Futagami et al., 1993; Greiner, 2005). Furthermore, energy consumption structure is investigated as the fifth driving factor in low-carbon economic development for its determinant role in setting the baselines of energy consumption and environmental pollution (Andrews-Speed, 2009; Bian et al., 2013a, 2013b).

Five testable research hypotheses regarding the relationships between each of the five factors and the low-carbon economic growth are proposed. Firstly, the "Pollution Haven Hypothesis" holds in China as China's relatively lax environmental regulation attracts the inflow of foreign investment in polluting sectors, which in turn increases the proportion of polluting sectors in industrial composition. Given the high correlation between the FDI location choice and foreign trade specialization, we hypothesize that foreign trades are carried out without accounting for the environmental cost impacts of policy regulation. Consequently, foreign trade can hinder the growth of low-carbon economic development. Environmental protections are public goods offered mostly by the public sectors rather than the private sectors, therefore we develop the hypothesis that increase of environment-related government expenditures contributes to a more sustainable development. As energy consumption and environmental pollution of the secondary sectors have much larger scales than the tertiary sectors do, we hypothesize that industrial structure upgrading leads to a more sustainable economic growth. Lastly, we hypothesize that adjustment of energy supply structure from the traditional fossil fuel dominated one to a clean energy supply composition with lower levels of carbon emission promotes the growth of low-carbon economy. Empirical analysis based on data from China positively supports all the afore-mentioned hypotheses except the one on foreign trade. Details of the empirical study using the data from 1998 to 2014 are given in Section 4.

Besides theoretical analysis, we also provide practical insights and policy implications for policy makers through the empirical study. Being a leading developing country, China currently undergoes a structural transition of industrialization and urbanization which makes it an ideal candidate for our case study. Hong and Sun (2011) argue that the rapid economic growth of China is mainly attributed to the accumulation of productive factors while technological progress plays no significant role. As the country with the largest energy consumption and greenhouse gas emissions, China strives to achieve a strategic balance among economic development, energy consumption and environmental protection (Bi et al., 2014). Policy makers in China have recognized the non-sustainability of its current mode of economic growth, and the necessity in explicitly accounting for the hidden costs associated with the lack of efficiency and quality. They are in search of solutions to a multi-objective problem of boosting the economy at a satisfactory rate, saving energy and protecting environment simultaneously. To achieve this goal and obtain a low-carbon economic development, Chinese government has initiated and implemented various policies, effectively shaping economic activities through regulatory policy guidance. In 2014, China lowered its CO_2 emissions per unit of GDP by 27% compared to the 2005 level and the share of non-fossil fuels in total primary energy supply reached 12.6% (IEA, 2016a).[2] Such dynamic changes in the economic development path and the policy-setting in China generate a rich dataset for conducting empirical analysis. It is important to note that the proposed framework for measuring and analyzing CWED is not specific to China. Our approach and discussion can be extended to analyze a much broader range of low-carbon economic issues in an international context.

The paper is organized as follows. In Section 2, we review the theoretical and empirical literatures which analyze indicators and measures relevant to economic development in a low-carbon system.

[2] http://www.iea.org/statistics/statisticssearch/report/?country=CHINA&product=renewablesandwaste&year=2014.

Section 3 proposes the definition of CWED and the quantitative CWED-measuring framework. A theory on the potential driving forces of CWED and the panel vector auto-regression model for the empirical analysis are presented in Section 4. Section 5 explains and interprets the results of the empirical analysis. Finally, we summarize the findings and conclude in Section 6.

2. Literature review on low-carbon economic development and its driving forces

2.1. Green growth

Various performance measures on economic development have been discussed in existing literature. Floyd (2013) presents a comprehensive and rational critique of traditional measures of economic growth and concludes that the traditional measures, for instance GDP, leave out many important factors, such as health impact, that are increasingly more important to citizens. Some studies incorporate such factors as society welfare, energy and environment into traditional measures. Warren (2010) establishes measures of environmentally sustainable development (ESD) using Green Star and NABERS rating schemes. Carley et al. (2011) propose an energy-based economic development (EBED) concept, which focuses on economic modeling using input/output techniques and analytical approaches. However, these studies only define an index without offering a quantitative approach to measure it.

2.2. Energy and environmental efficiency

Researchers have paid increasing attention to the issue of energy versus environmental impact efficiency evaluation, which is closely related to the problem of measuring economic performance while incorporating total factors in the production. Various approaches for measuring energy/environment efficiency have been proposed. One seminal approach is suggested by Pittman (1983), which incorporates undesirable outputs into an input/output productivity index. Other approaches, such as Stochastic Frontier Analysis (Cook and Seiford, 2009; Cullinane and Song, 2006), are insufficient in dealing with the modeling problems of having multiple outputs with some being undesirable.

Data envelopment analysis (DEA), first proposed by Charnes et al. (1978), is the dominant approach for measuring energy/environment performance of peer DMUs using a well-established linear programming approach with inputs and outputs. The DEA-Malmquist approach has been widely applied to evaluate total factor productivity in many fields, especially in energy and environmental research (Arabi et al., 2014; Yang and Yang, 2015) as it imposes no restriction on the forms of production function, nor assumptions for the underlying distribution of the inefficiency term. This strand of research mainly focuses on the following aspects: a) adopting the notion of total-factor energy efficiency (TFEE) introduced by Hu and Wang (2006), calculating the energy efficiency and examining the potential targets of energy saving or carbon emission through modified DEA methods (Bian et al., 2013a, 2013b; Ignatius et al., 2016; Li and Hu, 2012; Picazo-Tadeo et al., 2012; Suzuki and Nijkamp, 2016; Wu et al., 2015; Yao et al., 2015); b) using the DEA-Malmquist or DEA-Malmquist-Luenberger index to estimate the total factor energy productivity growth and dividing the index to find out the driving factors of the growth (Chang and Hu, 2010a, 2010b; Fan et al., 2015; Honma and Hu, 2009; Wu et al., 2012, 2013); c) investigating the factors which can influence the energy/environmental efficiency and total factor productivity by econometric tools (Chang and Hu, 2010a, 2010b; Fan et al., 2015).

2.3. Total factor productivity

In the realm of measuring economic growth, total factor productivity (TFP), the portion of outputs not explained by the amount of inputs used in production has long been studied and applied to explain the economic growth (Aigner et al., 1977; Kumbhakar, 1990; Solow, 1957; Van Beveren, 2012). Extensive research has been done on measuring the contributions of production factors and productivity change to economic growth since the work of Solow (1957). Empirical evidences find that TFP, rather than production factors accumulation, determines most of the cross-country differences in the level and growth rate of per capita income (Berument et al., 2012). Furthermore, TFP growth is an important source of overall economic growth (Bosworth and Collins, 2003; Easterly and Levine, 2001). The incremental contribution of the change of TFP to economic growth indicates the improvement of economic growth quality. In the process of quantifying TFP, DEA modeling approach shows more advantages than the traditional Solow model in dealing with multiple outputs including undesirable ones (Seiford and Zhu, 2002).

2.4. Driving forces of economic growth

Another relevant strand of research investigates the driving forces of economic growth which dates back in the early 1980s. Kuznets (1980) suggests that technological innovation, capital, structural shifts, national and international aspects are the driving forces of economic growth. Using panel data of OECD countries, Bassanini and Scarpetta (2001) identify driving forces of economic growth as capital, R & D, fiscal policy, financial development and international trade. In the existing research on analyzing the driving forces behind economic growth, the literature focusing on analyzing the drivers of low-carbon economic development is sparse. This is partly due to the lack of consensus on measurement and evaluation metrics for low-carbon economic development. For instance, Dou (2013) proposes that China shall implement a fully nature-oriented development scheme by adopting one of the following low-carbon development patterns: the single or the multi-regional linkage development pattern, or centrally-planned regulatory-policy driven development pattern corresponding to specific socio economic conditions. However, this conclusion lacks support from reliable empirical analysis. Nonetheless, theories and empirical methods of research on driving forces behind economic growth can be adopted to analyze low-carbon economic development issues. Following this approach, Herrerias and Orts (2011) conclude that, from the standpoint of endogenous growth theory, factors such as capital accumulation, level of free-trade and innovation activities are capable of generating sustainable productivity growth in the long-run.

To summarize, there is not yet a commonly agreed measure defined for evaluating economic development with low-carbon being one of the key considerations. Besides, the existing measures or indices based on the TFP theory focus predominantly on the energy or environmental efficiency while lacking the perspective of an overall measure on the efficiency of an entire low-carbon economic system.

3. Carbon-weighted economic development

3.1. Definition

We organize the different elements involved in defining CWED index along four dimensions—economy, energy, environment and resources through system analysis. We examine the interactions between different elements in a system and the manner in which the system behaves over time (Kondyli, 2010). The following analysis focuses on identifying components in each CWED dimension.

3.1.1. Economy

Economic development is an ongoing process of creating wealth and improving standards of living for people through deploying scarce resources to produce goods and services (Malizia, 1994). GDP is a commonly used measure of economic growth and social welfare (Hicks,

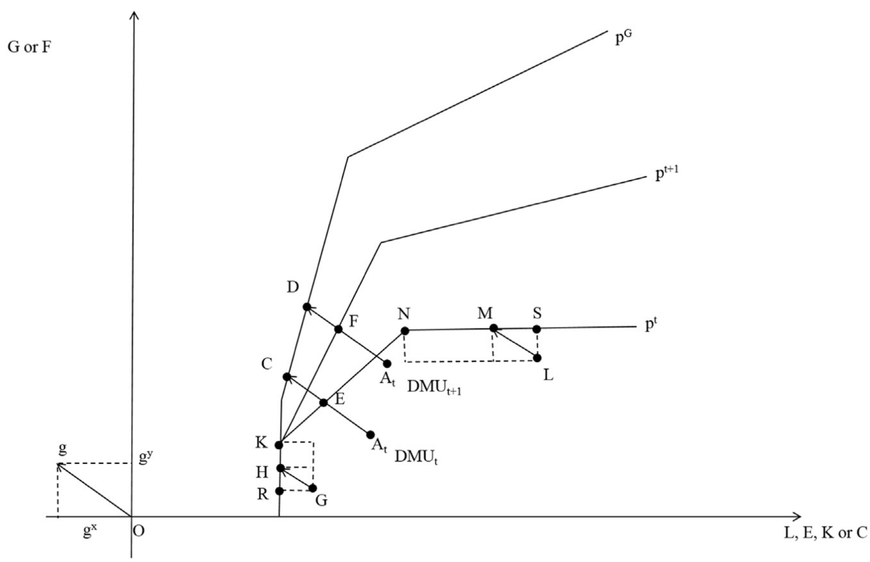

Fig. 1. Concept of the benchmark technology and directional distance function.

1940). The dynamics of the economic dimension is measured by GDP.

3.1.2. Energy

While energy is one of the factors, or resources, in the production process, we regard it as a separate dimension rather than one component of resources dimension to emphasize its significance in a low-carbon economy system, as fossil energy consumption can lead to destructive emissions of carbon dioxide and other pollutants. Total energy consumption is used as the measure in the energy dimension.

3.1.3. Environment

Environment has significant effects on the performance of economic activities and the well-being of people's living condition (Kondyli, 2010). Excessive energy use leads to not only global warming but also environmental issues (Omer, 2008). Carbon issues must be taken into consideration if we aim at developing economy and improving living standard. Both aspects of carbon issues are considered in this analysis: carbon source, which is the undesirable carbon emission of production, and carbon sequestration (specifically, carbon sink), which removes carbon dioxide from the atmosphere. Energy-based carbon emission and annual man-planted forestation area are respectively used to measure carbon emission and carbon sink.

3.1.4. Resources

Resources, or factors of production, are the inputs to the production process in which finished goods are produced to satisfy needs of people. Capital stock and labor are regarded as the two basic resources of production by the classical economic theories (Arrow and Chenery, 1961; Solow, 1957).

After identifying the four dimensions, we proceed to define CWED from an integrated perspective under the framework of total factor productivity to capture the improvement of economic growth quality. Specifically, CWED is defined as a function of labor (L), capital (K), energy consumption (E), GDP (G), carbon emission (C) and forestation area (F),

$$CWED = f(L, K, E, F, G, C) \tag{1}$$

where labor, capital and energy are conventional inputs, GDP and CO_2 are respectively desirable and undesirable outputs, and annual man-planted forestation area is a non-conventional input in that more forestation area is always preferred in a low-carbon economy. Annual man-planted forestation area is taken as an input since forest acts as a carbon sink that absorbs the carbon emission. It also serves as a proxy for the effort of a region in protecting the environment. However, it is different from the conventional inputs since a DMU with more forestation is considered more efficient when other input and output variables remain the same.

3.2. Measurement

Suppose there are J DMUs at time t. Each DMU uses three conventional inputs L, K, E and one non-conventional input F to produce one desirable output G and one undesirable output C. Under the conditions of weak disposability and null-jointness (Färe et al., 1989), the contemporaneous possible production technology at time t is formulated as follows.

$$\begin{aligned} P^t = \{&(L_t, K_t, E_t, F_t, G_t, C_t)\colon \textstyle\sum_{j=1}^{J} \lambda_{jt} L_{jt} \le L_t;\ \sum_{j=1}^{J} \lambda_{jt} K_{jt} \le K_t;\ \sum_{j=1}^{J} \lambda_{jt} E_{jt} \\ &\le E_t; \\ &\textstyle\sum_{j=1}^{J} \lambda_{jt} F_{jt} \ge F_t;\ \sum_{j=1}^{J} \lambda_{jt} G_{jt} \ge G_t;\ \sum_{j=1}^{J} \lambda_{jt} C_{jt} = C_t;\ \sum_{j=1}^{J} \lambda_{jt} = 1; \lambda_{jt} \ge 0;\ j \\ &= 1, 2\ldots J\} \end{aligned} \tag{2}$$

The contemporaneous benchmark technology constructs a reference production set at time t (Tulkens and Vanden, Eeckaut, 1995). Different from the contemporaneous benchmark technology, a global possible production technology is defined through enveloping all contemporaneous technologies and establishing a single reference possible production set from a panel data on inputs and outputs of all DMUs (Oh, 2010). This is illustrated in Fig. 1. The global possible production technology can be written as:

$$\begin{aligned} P^g = \{&(L_t, K_t, E_t, F_t, G_t, C_t)\colon \textstyle\sum_{j=1}^{J} \sum_{t=1}^{T} \lambda_{jt} L_{jt} \le L_t;\ \sum_{j=1}^{J} \sum_{t=1}^{T} \lambda_{jt} K_{jt} \\ &\le K_t;\ \textstyle\sum_{j=1}^{J} \sum_{t=1}^{T} \lambda_{jt} E_{jt} \le E_t; \\ &\textstyle\sum_{j=1}^{J} \sum_{t=1}^{T} \lambda_{jt} F_{jt} \ge F_t;\ \sum_{j=1}^{J} \sum_{t=1}^{T} \lambda_{jt} G_{jt} \ge G_t;\ \sum_{j=1}^{J} \sum_{t=1}^{T} \lambda_{jt} C_{jt} \\ &= C_t;\ \textstyle\sum_{j=1}^{J} \sum_{t=1}^{T} \lambda_{jt} = 1;\ \lambda_{jt} \ge 0;\ j = 1, 2\ldots J\} \end{aligned} \tag{3}$$

Compared with the traditional radial DEA approach for measuring the efficiency of DMUs, DDF is able to handle the undesirable outputs in measuring the inefficiency of DMUs by seeking the maximum non-radial expansion in outputs and non-conventional inputs and contraction in inputs and undesirable outputs simultaneously given a directional vector. The directional vector g_O, determines the direction in which desirable outputs and non-conventional inputs expand, and undesirable outputs and conventional inputs shrink.

Suppose DMU A is at point A_t and point A_{t+1} at two different time periods t and $t+1$, respectively. We introduce the following definitions.

(1) The directional distance between point A and the global benchmark technology at time t is $\overrightarrow{D^G}(L_t, K_t, E_t, F_t, G_t, C_t)$;
(2) The directional distance between point A and the contemporaneous benchmark technology at time t is $\overrightarrow{D^t}(L_t, K_t, E_t, F_t, G_t, C_t)$.

Based on the concept of MPL index (Chung et al., 1997), CWED is defined as:

$$CWED^{t,t+1} = \frac{1+\overrightarrow{D^G}(L_t, K_t, E_t, F_t, G_t, C_t)}{1+\overrightarrow{D^G}(L_{t+1}, K_{t+1}, E_{t+1}, F_{t+1}, G_{t+1}, C_{t+1})} \tag{4}$$

$CWED^{t,t+1} > (<)\ 1$ means that the directional distance between the DMU's location at time t and the global benchmark technology is larger (smaller) than that at time $t+1$, therefore indicating TFP gain (loss). To fully understand CWED, we decompose it as follows.

$$\begin{aligned} CWED^{t,t+1} &= \frac{1+\overrightarrow{D^G}(L_t, K_t, E_t, F_t, G_t, C_t)}{1+\overrightarrow{D^G}(L_{t+1}, K_{t+1}, E_{t+1}, F_{t+1}, G_{t+1}, C_{t+1})} \\ &= \frac{1+\overrightarrow{D^t}(L_t, K_t, E_t, F_t, G_t, C_t)}{1+\overrightarrow{D^{t+1}}(L_{t+1}, K_{t+1}, E_{t+1}, F_{t+1}, G_{t+1}, C_{t+1})} \\ &\times \frac{\frac{1+\overrightarrow{D^G}(L_t, K_t, E_t, F_t, G_t, C_t)}{1+\overrightarrow{D^t}(L_t, K_t, E_t, F_t, G_t, C_t)}}{\frac{1+\overrightarrow{D^G}(L_{t+1}, K_{t+1}, E_{t+1}, F_{t+1}, G_{t+1}, C_{t+1})}{1+\overrightarrow{D^{t+1}}(L_{t+1}, K_{t+1}, E_{t+1}, F_{t+1}, G_{t+1}, C_{t+1})}} \\ &= CWEEC^{t,t+1} \times CWETP^{t,t+1} \end{aligned} \tag{5}$$

where $CWEEC^{t,t+1}$ (Carbon-weighted Economic Efficiency Change) measures the technical efficiency change from time t to time $t+1$, and $CWETP^{t,t+1}$ (Carbon-weighted Economic Technical Progress) best represents the gap change between the two time periods and measures the technical frontier change from time t to time $t+1$. Intuitively, in Fig. 1, point A_t and A_{t+1} correspond to the respective locations of DMU A at time t and time $t+1$. Then CWED of A from time t to time $t+1$ can be represented as $\frac{1+A_tC}{1+A_{t+1}D} = \frac{1+A_tE}{1+A_tF} \times \frac{\frac{1+A_tC}{1+A_tE}}{\frac{1+A_{t+1}D}{1+A_tF}}$.

To calculate CWED and its decompositions, we need to obtain the directional distances to represent the inefficiency. However, the traditional method of DDF does not incorporate slacks of inputs and outputs even though it has many desirable features (Cooper et al., 2007). Fukuyama and Weber (2009) propose a directional slacks-based measure of technical inefficiency (DSBI) accounting for all slacks in the input and output constraints by incorporating directional vectors into the slacks-based measure (SBM). SBM was first proposed by (Tone, 2001). Fig. 1 also illustrates the enhancement of DSBI compared with traditional DDF. Intuitively, the inefficiency of point G and L are $\frac{GH}{g_0}$ and $\frac{LM}{g_0}$, respectively measured by DDF. The efficient reference points are H and M. However, according to the technical frontier P^t bounded to the northwest by RKNS, point H can still expand GDP and forestation to point K keeping inputs invariant. Likewise, it is better off from point M to point N. DSBI solves this problem by adding slacks defining the production technology, see Eq. (6) and Eq. (7). Under the condition of DSBI, the efficient reference points would be K and N for point G and L, respectively. The corresponding inefficiency is then represented by $\frac{\frac{RG}{g_{L,E,KorC}}+\frac{RK}{g_{GorF}}}{2} = \frac{GH}{g_0} + \frac{KH}{2g_{GorF}}$ for point G and $\frac{\frac{SN}{g_{L,E,KorC}}+\frac{LS}{g_{GorF}}}{2} = \frac{LM}{g_0} + \frac{MN}{2g_{L,E,KorC}}$ for point L. It is also shown that DSBI collapses to DDF when the slacks are zero. Indeed, DSBI generalizes most of the existing measures of inefficiency, e.g. Directional Russell Measure of Inefficiency (Färe and Knox Lovell, 1978) and Range-Adjusted Measure of Inefficiency (Cooper et al., 1999).

In this analysis, we modify the original DSBI model by incorporating non-conventional inputs and undesirable outputs, and propose a directional slacks-based measure at time t as follows:

$$\begin{aligned} &\overrightarrow{D^t}(L_{0t}, K_{0t}, E_{0t}, F_{0t}, G_{0t}, C_{0t}; g) = \max_{s_t^L, s_t^K, s_t^E, s_t^F, s_t^G, s_t^C, \lambda} \frac{1}{4}\Big[\frac{1}{3}\Big(\frac{s_t^L}{g_t^L} + \frac{s_t^K}{g_t^K} + \frac{s_t^E}{g_t^E}\Big) + \frac{s_t^F}{g_t^F} + \frac{s_t^G}{g_t^G} + \frac{s_t^C}{g_t^C}\Big] \\ &s.\ t.\ L_{0t} = \textstyle\sum_{j=1}^J \lambda_{jt} L_{jt} + s_t^L,\ t = 1, 2\ldots T;\ K_{0t} = \sum_{j=1}^J \lambda_{jt} K_{jt} + s_t^K,\ t = 1, 2\ldots T; \\ &E_{0t} = \textstyle\sum_{j=1}^J \lambda_{jt} E_{jt} + s_t^E,\ t = 1, 2\ldots T;\ F_{0t} = \sum_{j=1}^J \lambda_{jt} F_{jt} - s_t^F,\ t = 1, 2\ldots T; \\ &G_{0t} = \textstyle\sum_{j=1}^J \lambda_{jt} L_{jt} - s_t^G,\ t = 1, 2\ldots T;\ C_{0t} = \sum_{j=1}^J \lambda_{jt} C_{jt} + s_t^C,\ t = 1, 2\ldots T; \\ &s_t^L, s_t^K, s_t^E, s_t^F, s_t^G, s_t^C \ge 0;\ \textstyle\sum_{j=1}^J \lambda_{jt} = 1; \lambda_{jt} \ge 0; \forall\, j, \forall\, t. \end{aligned} \tag{6}$$

where L_0, K_0, E_0, F_0, G_0 and C_0 are vectors of the inputs and outputs of the targeted DMU_0. g^L, g^K, g^E, g^F, g^G and g^C are the respective positive directional vectors for decreasing conventional inputs, increasing non-conventional input, increasing desirable output and decreasing undesirable output. s^L, s^K, s^E, s^F, s^G, and s^C denote the vectors of the corresponding slacks. Similarly, under the global possible production technology, the global directional slacks-based measure is obtained as follows:

$$\begin{aligned} &\overrightarrow{D_0^G}(L_{0t}, K_{0t}, E_{0t}, F_{0t}, G_{0t}, C_{0t}; g) = \max_{s_t^L, s_t^K, s_t^E, s_t^F, s_t^G, s_t^C, \lambda} \frac{1}{4}\Big[\frac{1}{3}\Big(\frac{s_t^L}{g_t^L} + \frac{s_t^K}{g_t^K} + \frac{s_t^E}{g_t^E}\Big) + \frac{s_t^F}{g_t^F} + \frac{s_t^G}{g_t^G} + \frac{s_t^C}{g_t^C}\Big] \\ &s.\ t.\ L_{0t} = \textstyle\sum_{j=1}^J \sum_{t=1}^T \lambda_{jt} L_{jt} + s_t^L,\ t = 1, 2\ldots T;\ K_{0t} = \sum_{j=1}^J \sum_{t=1}^T \lambda_{jt} K_{jt} + s_t^K,\ t = 1, 2\ldots T; \\ &E_{0t} = \textstyle\sum_{j=1}^J \sum_{t=1}^T \lambda_{jt} E_{jt} + s_t^E,\ t = 1, 2\ldots T;\ F_{0t} = \sum_{j=1}^J \sum_{t=1}^T \lambda_{jt} F_{jt} - s_t^F,\ t = 1, 2\ldots T; \\ &G_{0t} = \textstyle\sum_{j=1}^J \sum_{t=1}^T \lambda_{jt} G_{jt} - s_t^G,\ t = 1, 2\ldots T;\ C_{0t} = \sum_{j=1}^J \sum_{t=1}^T \lambda_{jt} C_{jt} + s_t^C,\ t = 1, 2\ldots T; \\ &s_t^L, s_t^K, s_t^E, s_t^F, s_t^G, s_t^C \ge 0;\ \textstyle\sum_{j=1}^J \sum_{t=1}^T \lambda_{jt} = 1;\ \lambda_{jt} \ge 0; \forall\, j, \forall\, t. \end{aligned} \tag{7}$$

The directional vector $g = (g^L, g^K, g^E, g^F, g^G, g^C)$ is fixed and given, for instance, by decision-makers. The chosen directional vectors are:

$$\begin{aligned} &g_t^L = L_t^{\max} - L_t^{\min},\ g_t^K = K_t^{\max} - K_t^{\min},\ g_t^E = E_t^{\max} - E_t^{\min}, \\ &g_t^F = F_t^{\max} - F_t^{\min},\ g_t^G = G_t^{\max} - G_t^{\min},\ g_t^C = C_t^{\max} - C_t^{\min}. \end{aligned} \tag{8}$$

With these directional vectors, the directional slacks-based measure has been shown to satisfy some desirable properties, such as non-negativity, Pareto-Koopman's efficiency, invariance, homogeneity of degree minus one and weak translation (Fukuyama and Weber, 2009).

4. Driving forces behind carbon-weighted economic development

4.1. The potential driving forces: theories and empirical evidences

This session analyzes the potential driving forces behind CWED based on relevant theories and empirical evidences. We are in particular concerned with whether these driving factors influence CWED in both short and long-run. Hypotheses about the relationships between the driving factors and low-carbon economic development are proposed.

Hypothesis 1. FDI growth in developing countries hinders the growth of low-carbon economic development. The relationship between FDI and economic growth has been widely studied. A substantial body of empirical evidences suggest that FDI has a positive effect on economic growth (Borensztein et al., 1998; Akinlo, 2004; Mehic et al., 2013). While some studies show that FDI has no significant effect or even negative effect on economic growth (Mencinger, 2003). On one hand, FDI effects economic growth through a direct way by increasing savings and investments of the host country to make net contribution to capital stock. On the other hand, FDI can drive economic growth through an indirect way by encouraging local diffusion of knowledge and innovation to contribute to knowledge stock of the host country. When it comes to the relationship between FDI and the low carbon economic growth, the effect of FDI on the energy consumption and environmental pollution shall be taken into account. The "Pollution Haven Hypothesis" (Eskeland and Harrison, 2003) states that firms which choose to physically invest in foreign countries tend to locate in the countries with fewer stringent environmental regulations, and thus making their host countries suffering from high levels of energy consumption and environmental pollution. The empirical evidences of "Pollution Haven Hypothesis" in China have been mixed. He (2005) contrasts a simultaneous model to study the FDI-emission nexus in China, providing evidence for "Pollution Haven Hypothesis". This research also finds an indirect impact of FDI on emission through its influence on the host economy's industrial composition. A study implementing multivariate granger causality between CO_2, energy consumption, FDI and GDP of BRIC countries also concludes that there exists strong bidirectional causality between emission and FDI, supporting the hypothesis (Pao and Tsai, 2011). Using firm-level data of China, Fisher-Vanden et al. (2006) argue that FDI and in-house R & D enhance the energy-saving effect of each other, for FDI firms which are R & D intensive tend to employ more energy-efficient technologies. Since the environmental issues are the main focus of this study, we hypothesize that the negative effect of FDI on the low-carbon economic development of developing countries would dominate the positive effect.

Hypothesis 2. Foreign trade growth makes the low-carbon economic development worse off. Many studies in the literature conclude that magnitude of free-trade positively affects economic growth (Aydin Okuyan et al., 2012; Badinger, 2005; Dollar, 1992; Edwards, 1998), while others set forth the negative effects of trade on economic growth (Galindo et al., 2007). Endogenous growth theories argue that trade can increase economic growth through expansion effect or technology transfer. In an open free-trade economy, domestic sectors try to maintain technological progress in order to compete with foreign goods and services (Aydin Okuyan et al., 2012). It has been argued that international trade policies promoting economic growth may overlook the negative environmental impacts of free-trade (Suri and Chapman, 1998). International trades may have been negatively affecting the environment in China as lots of energy-intensive products consumed in developed countries have been produced in China. Such arguments lead to the hypothesis that increase in foreign trade may cause a decline in the quality of economic growth of China.

Hypothesis 3. Increase of government expenditure has a positive effect on the economic development growth. The relationship between industrial structure and economic growth has remained in the spotlight of industry theory for a long time (Lande, 1994; Shaffer, 2009). Observations suggest that change in industrial structure is closely related to economic growth in China in the long-term (Dong et al., 2011). Industrial structure upgrading in an economy refers to that the core part of the industrial structure transfers to the tertiary sector from the primary and secondary sectors. Industrial structure changes may influence overall economic efficiency and thus promoting the economic growth as the levels of energy consumption and environmental pollution of secondary sector are much higher than those of the tertiary sectors. Therefore, industrial structure upgrading would lead to a more sustainable economic growth.

Hypothesis 4. Industrial structure upgrade can boost the growth of low-carbon economic development. The relationship between public expenditure and economic growth has been studied since the 1990s (Barman and Gupta, 2010; Barro, 1990; Futagami et al., 1993; Greiner, 2005). Barro (1990) introduces government expenditure into endogenous economic growth model. Public expenditure contributes to capital accumulation and thus promotes the economic growth. At the same time, an increase of public expenditure would lead to tax increase, which reduces the benefits of taxpayers and lowers the economic growth (Vu Le and Suruga, 2005). Environmental protections are public goods which are offered mostly by government rather than market. As a result, the increase of government expenditures to conserve energy and protect environment, or to develop energy-saving technologies would contribute to a more sustainable development.

Hypothesis 5. Optimization of the energy consumption structure to a cleaner level positively supports the growth of low-carbon economy. The relationship between energy consumption and economic growth is the focal point of energy and environment issues (Chen et al., 2012; Chontanawat et al., 2008; Ghali and El-Sakka, 2004; Tsani, 2010). Whether it is possible to maintain a sustainable economic growth without increasing energy consumption is widely discussed (Hwang and Yoo, 2014). GDP may be spurred by energy-intensive industries, whose development would consume much more energy. Excessive energy consumption would lead to greenhouse gas emissions and hinder the low carbon economic growth. Our focus is more on the energy consumption structure rather than total consumption, because total consumption is already an input factor in CWED. As carbon emission levels of different energy supply sources differ, balancing the energy structure by reducing energy supply from traditional fossil fuel and promoting new energy development shall be helpful for carbon emission reduction. Improving the low carbon development through adjusting energy supply structure is suggested by many researchers (Andrews-Speed, 2009; Bian et al., 2013a, 2013b; Dou, 2013). Our hypothesis is that a cleaner energy demand structure would boost the low-carbon economic development.

In order to find out the role of these key economic variables in determining the low-carbon economic growth and tackle the endogeneity between the economic variables, we employ a panel vector auto-regression (PVAR) approach. The PVAR model allows us to analyze the endogenous interactions and dynamical behaviors between variables in the system by taking into account the fact that one variable in low carbon system may be influenced by not only other factors, but also lagged value of all factors including itself for a long period, i.e. the time lag effect.

4.2. Panel vector auto-regression (PVAR) model

PVAR suggested by Holtz-Eakin et al. (1988), combines the conventional VAR approach with the panel data approach. PVAR treats all variables as endogenous as well as allows for an individual-specific unobserved heterogeneity. Besides that, a reduced-form of VAR approach relaxes the strong assumptions made in traditional economy growth theory (Love and Zicchino, 2006). Orthogonalized impulse-response functions can be analyzed to separate the response of CWED to shocks in fundamental economic factors. In addition, PVAR model estimated by generalized method of moment (GMM) relaxes the requirements for statistical distribution characteristics of sample data due to the robustness property of GMM estimators.

Following a common approach in the PVAR methodology, the dynamic interactions among variables in our estimation are specified in the following model:

$$y_{i,t} = \alpha_i + \beta_0 + \sum_{j=1}^{p} \beta_j y_{i,t-j} + \upsilon_t + u_{i,t} \tag{9}$$

where β_0 is a vector of constant terms, β_j is a matrix of coefficients, α_i is the individual effect, capturing the improvement of economic growth quality rather than growth quantities, ϑ_t is the time effect, μ_{it} is the individual effect at time t, and p is the optimal lag order selected such that the error terms are serially uncorrelated. $y_{i,t}$ is a vector of {*LnCWED, EnergyStruc, DLnFiscal, DLnFDI, DLnTrade, DLnIndusStruc*} for DMU i (30 provinces in China), which represents the natural logarithm of carbon-weighted economic development, the ratio of coal consumption to total primary energy consumption, the differential logarithmic form of the ratio of local fiscal expenditures to GDP, the differential logarithmic form of the ratio of foreign direct invest to GDP, the differential logarithmic form of the ratio of total foreign trades to GDP and the differential logarithmic form of industrial structure (i.e. the ratio of the added value of service sector to that of industrial sector). We use the differential logarithmic form of the variables, as CWED measures the growth of the low-carbon performance, which can be written as:

$$Lowcarboneconomyperformance^t = \frac{1}{1 + \overrightarrow{D^G}(L_t, K_t, E_t, F_t, G_t, C_t)}. \quad (10)$$

Then the natural logarithm of CWED is expressed as:

$$LnCWED_{t,t+1} = Ln(Lowcarboneconomyperformance^{t+1}) - Ln(Lowcarboneconomyperformance^{t}). \quad (11)$$

As *LnCWED* is equal to the differential logarithmic form of the low-carbon economy performance, we use the differential logarithmic form of other variables to represent their growth rates to make the values consistent with the meaning of *LnCWED*. However, the original form of energy consumption structure is used since the primary energy resource endowment of China is characterized by rich coal. Thus, it is difficult to change the energy structure in the short-term (Wu and Zhang, 2016). The fixed-effects estimator is not consistent in a dynamic panel since fixed effects are correlated with the regressors due to the lags of dependent variables. Thus a forward mean differencing method (the Helmert procedure) is implemented to all the variables. In this orthogonal deviation transformation, each observation is expressed as a deviation from average of future observations to remove the fixed effects. This transformation preserves homoscedasticity and does not induce serial correlation (Arellano and Bover, 1995). After regression, we analyze the dynamic behavior of PVAR model using the impulse response function (IRF). The IRF is able to identify the effects of one-standard-deviation shock in a variable on the adjustment path as well as the size and characteristics of the effects.

5. Results and analysis

5.1. Data

A two-stage procedure is employed to dynamically analyze low-carbon economic development of China and its driving forces. First, we apply the CWED index to measure the low carbon economic development of 30 provinces (Tibet is not included because its data is not available for many years) in China from 1998 to 2014. Second, we apply the PVAR model to explore the dynamic relationships among CWED, FDI, trades, industrial structure, local fiscal expenditures and energy consumption structure. Data used in this session is described in Table 1.

5.2. Carbon-weighted economic development in China

For comparison purposes, we implement the modified DSBI proposed in this section and the traditional DDF in Chung et al. (1997) using the same dataset to demonstrate the difference in inefficiency estimation. Results shown in Table 2 illustrate clearly that the inefficiency is underestimated by the DDF approach, for DDF does not

Table 1
Variables description.

	Category	Variable	Unit	Source	Data Processing
Stage 1	Conventional Inputs	Labor	10^4 Persons	China Statistical Yearbook	Employing the actual number of workers since data on working hours are not available.
		Capital stock	10^8 RMB	China Statistical Yearbook	The initial data of 1998 is from Shan (2008) and the data after 1998 is estimated by the perpetual inventory method. All the data have been converted into 1952 constant prices.
		Energy consumption	10^4TEC	China Energy Statistical Yearbook	Using the data of the total energy consumption.
	Non-conventional input	Annual man-planted forestation area	10^3 ha	China Statistical Yearbook China Forestry Statistical Yearbook	Using the data measures of total area of newly increased forest, woods and shrub forest that are man-planted.
	Desirable Output	GDP	10^8 RMB	China Statistical Yearbook	The real GDP on 1998 constant prices.
	Undesirable Output	Carbon emission	10^4Tons	China Energy Statistical Yearbook	Employing the approach recommended by IPCC to multiply the consumption of coal (two kinds), oil (four kinds), natural gas by emission factors suggested by IPCC (2006) .
Stage 2	Driving factors	FDI	–	China Statistical Yearbook	Calculating the ratio of FDI to GDP and putting it into differential logarithmic form.
		Foreign trade	–	China Statistical Yearbook	Calculating the ratio of total import and export trades to GDP and putting it into differential logarithmic form.
		Industrial structure	–	China Statistical Yearbook	Calculating the ratio of the added value of service sector to that of industrial sector and putting it into differential logarithmic form.
		Local fiscal expenditure	–	China Statistical Yearbook	Calculating the ratio of local fiscal expenditures to GDP, and putting it into differential logarithmic form.
		Energy consumption structure	%	China Statistical Yearbook	Calculating the ratio of coal consumption to total energy consumption to imply the primary energy consumption structure.

Table 2
Summary statistics of inefficiency estimates.

Time	Measure	NO.	Mean	Standard deviation	Min	Max	Efficient province (%)
1998–2002	Inefficiency by DDF	150	0.02	0.02	0	0.10	67(44.67%)
	Inefficiency by DSBI	150	0.06	0.07	0	0.29	67(44.67%)
2003–2007	Inefficiency by DDF	150	0.01	0.02	0	0.13	83(55.33%)
	Inefficiency by DSBI	150	0.04	0.06	0	0.25	83(55.33%)
2008–2014	Inefficiency by DDF	210	0.02	0.03	0	0.13	92(43.81%)
	Inefficiency by DSBI	210	0.06	0.07	0	0.24	92(43.81%)
Global 1998–2014	Inefficiency by DDF	510	0.02	0.02	0	0.15	64(12.55%)
	Inefficiency by DSBI	510	0.12	0.09	0	0.33	64(12.55%)

Table 3
CWED, CWETP and CWEEC of China (1999–2014).

Index		CWED			CWETP			CWEEC		
Region	Province/Year	1999/2002	2003/2007	2008/2014	1999/2002	2003/2007	2008/2014	1999/2002	2003/2007	2008/2014
East area	Beijing	1.005	0.998	1.012	1.005	0.998	1.012	1.000	1.000	1.000
	Tianjin	1.004	1.004	1.008	1.004	1.004	1.008	1.000	1.000	1.000
	Hebei	1.007	0.980	1.005	1.050	0.986	1.003	0.961	1.008	1.002
	Liaoning	1.017	1.013	1.000	1.017	1.013	1.000	1.000	1.000	1.000
	Shanghai	1.009	1.007	1.011	1.009	1.007	1.011	1.000	1.000	1.000
	Jiangsu	1.009	1.000	1.029	0.998	1.001	1.019	1.011	1.000	1.011
	Zhejiang	0.999	0.992	1.010	1.008	0.987	1.012	0.991	1.005	0.999
	Fujian	1.003	0.996	1.004	1.003	0.996	1.004	1.000	1.000	1.000
	Shandong	1.004	0.988	1.011	1.041	0.960	1.015	0.965	1.031	1.004
	Guangdong	1.022	1.010	1.003	1.022	1.010	1.003	1.000	1.000	1.000
	Hainan	0.998	0.998	0.999	0.998	0.998	0.999	1.000	1.000	1.000
	East average	1.007	0.999	1.008	1.014	0.996	1.008	0.993	1.004	1.001
Central area	Shanxi	1.000	0.973	0.997	1.004	0.971	0.996	0.996	1.016	1.002
	Inner Mongolia	1.008	0.981	0.997	1.008	0.981	0.997	1.000	1.000	1.000
	Jilin	1.003	0.980	1.010	0.998	0.977	1.006	1.005	1.003	1.004
	Heilongjiang	1.005	0.987	1.006	1.011	0.983	1.009	0.995	1.005	0.997
	Anhui	1.016	0.986	1.023	0.985	0.993	1.010	1.032	0.994	1.015
	Jiangxi	1.000	0.986	0.999	0.996	0.971	1.008	1.004	1.015	0.991
	Henan	1.002	0.981	1.011	1.013	0.991	1.002	0.989	0.993	1.008
	Hubei	1.004	0.989	1.007	1.003	0.985	1.003	1.001	1.004	1.005
	Hunan	1.014	0.985	1.014	0.990	0.987	0.999	1.025	0.999	1.016
	Guangxi	1.010	0.982	0.996	0.996	0.976	1.004	1.014	1.006	0.993
	Central average	1.006	0.983	1.006	1.000	0.982	1.003	1.006	1.004	1.003
West area	Chongqing	1.011	0.987	1.008	0.992	0.982	1.005	1.019	1.005	1.002
	Sichuan	1.032	0.970	0.997	1.032	0.970	1.017	1.000	1.002	0.980
	Guizhou	1.028	0.959	1.005	1.011	0.957	0.997	1.017	1.002	1.009
	Yunnan	1.000	0.986	1.011	1.000	0.986	1.011	1.000	1.000	1.000
	Shaanxi	1.017	0.966	0.999	1.008	0.972	1.001	1.009	0.994	0.998
	Gansu	1.005	0.981	0.997	1.001	0.973	1.000	1.004	1.009	0.998
	Qinghai	1.000	0.992	1.006	1.000	0.992	1.006	1.000	1.000	1.000
	Ningxia	1.000	0.986	0.997	1.000	0.986	1.005	1.000	1.000	0.992
	Xinjiang	1.014	0.985	0.988	1.003	0.979	1.002	1.011	1.006	0.986
	West average	1.012	0.979	1.001	1.005	0.977	1.005	1.007	1.002	0.996
Average		1.008	0.988	1.005	1.007	0.986	1.005	1.002	1.003	1.000

account for the remaining overuse of inputs and under-production of outputs due to slacks in the technological constraints. Thus, the modified DSBI approach identifies more appropriate reference efficient points on the frontiers for DMUs than the DDF approach does.

Table 3 and Fig. 2 report the results of CWED for 30 provinces of China from 1999 to 2014. China experienced a highly rapid economic growth during the period of 2003–2007 at the GDP growth rate over 10% every year. After that, financial crisis affected regions in China from 2008 and China stepped into the economic transformation stage with energy-saving and emission-reduction. Considering the fact of these three stages of development we divide the research period into three parts: 1998–2002, 2003–2007 and 2008–2014. In Table 3, the average value of CWED are greater than 1 in the periods of 1998–2002 and 2008–2014, indicating that these two periods saw the improvement in low carbon economic development in China. However, the average value of CWED is less than 1 in the period of 2003–2007, illustrating a decline of low carbon economic growth.

For the period of 1998–2002, 28 provinces experienced carbon-weighted economic development growth, attesting that China maintained a balanced low carbon economic development. Considerations over the balancing of pure economic growth, energy conservation and environment protection were coordinated. The west region had a higher average CWED followed by the east region and central region. During this period, all the regions are almost in the same path to increase the low-carbon economic development by making technical progress and improving technical efficiency simultaneously.

For the period of 2003–2007, the unprecedented high-speed development of economy in China was driven by the torrid growth of the energy-intensive industries, such as iron and steel industry and cement industry. Energy-saving and environment-protecting were neglected in this unsustainable pattern of economic growth. It was a backward step in a low-carbon perspective, even though the annual GDP growth was over 10%. During this period, all the three regions suffered from a decrease of CWED. However, the technical efficiency still grew, accompanied by the technical progress reducing a lot, which meant the low-carbon economy production frontier retrogressed. GDP booming at

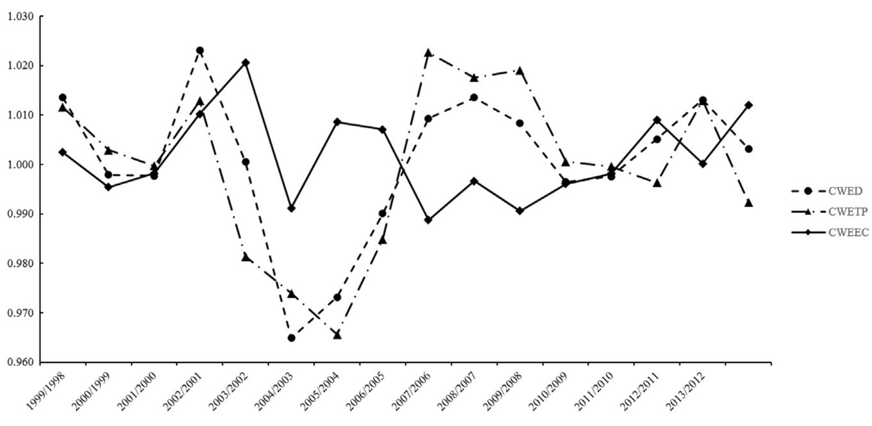

Fig. 2. The carbon-weighted economic development in China (1999–2014).

this stage was the result of resource consuming, rather than the technology development. For the period of 2008–2014, 20 provinces experienced carbon-weighted economic development growth. This is because since 2006 China has been making great efforts to develop into a low-carbon economy pattern. The number of policies related to improve energy efficiency had a great leap in 2006 (IEA, 2016b).[3] Due to the lag effect of policy, the production frontier has improved significantly, promoting the low-carbon economic development to a new stage during 2008–2014. East region kept growing the fastest since 2003, starting the regional inequitable growth of low-carbon economic development in China.

5.3. Driving Forces behind CWED

5.3.1. Panel unit root results

The presence of non-stationary behavior may result in spurious regressions, which makes the estimates biased, or even invalid in PVAR model and IRF analysis. Table 4 presents the estimated results of unit root tests with three approaches. The results show that all statistics are significant revealing the six variables in low-carbon economy system are stationary.

5.3.2. PVAR(6) estimates

Determining the optimal lag length is another necessary step before the PVAR estimation model is performed. A too long lag length can distort the data and lead to a decrease in power, while a too short lag length may not capture the dynamic behaviors of the variables in VAR system (Hendry and Juselius, 2001). We use three criteria to choose the optimal lag length, AIC (Akaike information criterion), BIC (Bayesian information criterion) and HQIC (Hannan and Quinn information criterion). Table 5 shows the results of the PVAR(6) lag order selection criteria. As we prefer a parsimonious model specification, the PVAR(6) model with the lag length of one is chosen.

Table 6 provides the results of the PVAR(6), with six endogenous variables estimated by GMM. We focus on the first equation in which *LnCWED* is the dependent variable. The results show that primary energy consumption structure, fiscal expenditure growth rate and industrial upgrade rate in the last year have significant effects on low-carbon economic development directly. This empirical evidence positively supports Hypotheses 3, 4 and 5. A province with a lower ratio of coal in the primary energy consumption is more likely to have a higher CWED in the next year. Besides, a higher degree of industrial transformation from the secondary sector to the tertiary sector would also boost the development of low-carbon economy growth. In addition, increasing the ratio of the fiscal expenditure to GDP is also beneficial for the CWED in the following year, illustrating that the increase of the benefits from public expenditure influences more than the reduction of taxpayers' benefits in China.

The growth of the ratio of FDI and foreign trade to GDP do not show a direct effect on CWED. However, these two variables can have indirect effects on CWED through industrial structure change. A region with a higher FDI increase hinders the growth of industrial upgrade thus imposing a negative effect on CWED. To some extent, this result supports the "Pollution Haven Hypothesis" in China. What is more, the lagged variable of industrial upgrade also has a negative effect on FDI, revealing that an industry structure characterized by service sector is less attractive to FDI in China. The up-to-date empirical data positively supports Hypothesis 1.

On the contrary, foreign trade growth brings benefits to the upgrade of industrial structure, which implies that an outward-oriented economy is easier to develop low-carbon economy through technological progress. Moreover, a province with more trade will expand the government expenditure to ensure the social welfare when there is a shock from outside. This result is consistent with the compensatory hypothesis that a more outward-oriented province would expand its government expenditure to provide better social welfare, as the deepened globalization exposes an economy to more unstable conditions (Garrett, 1998; Rodrik, 1997). By these two indirect paths, the increase of trade brings a positive effect on CWED and this rejects Hypothesis 2.

5.3.3. Impulse response results

The impulse response is predicted in ten benchmarks and used to analyze the dynamic relationships among the six variables in the low-carbon economy system (see Fig. 3). The horizontal axis shows the number of years after the shock. The vertical axis shows the deviation from the baseline level of the former variable in the title in response to a one-standard deviation change of the shock variable (the latter one). The area between the blue line and green line is the 95% confidential interval. Only when this area is all above or below zero, we can conclude that the impulse response (i.e. red line) is statistically significant at the 5% level.

Following the approach of Love and Zicchino (2006) in analyzing the results of PVAR estimation, we specifically analyze two dynamic effects: (1) Direct Effects, the response of *LnCWED* to the shock of other five variables; (2) Feedback Effects, the response of the other five variables to the shock of *LnCWED*.

5.3.3.1. Direct effect. The direct effect of *LnCWED* is shown in the first row of Fig. 3. First, the shock of energy structure has a negative effect on CWED in the first year with the maximum at the level of 0.6%. After that, the negative effect is still lasting and slowly converges to the original level, which indicates that the primary energy consumption structure endowment of a province would have an enduring influence on CWED. Second, the fiscal expenditure ratio growth has a positive effect on CWED, however, it reaches the peak in the first year and decreases sharply in the second year. This implies that the fiscal

[3] http://www.iea.org/policiesandmeasures/energyefficiency/?country=China.

Table 4
Panel unit root test result.

Test	Null Hypothesis	*LnCWED*	*EnergyStruc*	*DLnFiscal*	*DLnFDI*	*DLnTrade*	*DLnIndusStruc*
LLC	H0: The variables are non-stationary	−15.505***	−2.865**	−12.729***	−15.070***	−12.730***	−8.543***
Fish ADF		13.415***	8.648***	16.525***	14.739***	11.978***	9.608***
IPS		−13.855***	−1.350*	−11.897***	−13.755***	−11.567***	−7.964***

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Table 5
PVAR(6) lag order selection criteria.

Lag	AIC	BIC	HQIC
1	−13.84	−11.7621[a]	−13.0187[a]
2	−13.9524	−11.3897	−12.9365
3	−14.2102	−11.1013	−12.9741
4	−14.4578[a]	−10.7278	−12.9699

[a] Indicate lag order selected by the criterion.

Table 6
Results of the PVAR(6) estimates.

Independent variables	Dependent variables					
	LnCWED	*EnergyStruc*	*DLnFiscal*	*DLnFDI*	*DLnTrade*	*DLnIndusStruc*
h_LnCWED	0.0227	0.0257	−0.0745	−0.118	−0.0809	0.13
	(−0.0991)	(−0.0254)	(−0.134)	(−0.445)	(−0.328)	(−0.116)
h_EnergyStruc	−0.313***	0.887***	0.455**	−0.346	1.955***	−1.196***
	(−0.113)	(−0.0552)	(−0.225)	(−0.994)	(−0.611)	(−0.302)
h_DLnFiscal	0.0969***	−0.0196	0.259***	0.470*	−0.0417	0.0413
	(−0.0242)	(−0.0185)	(−0.0658)	(−0.279)	(−0.165)	(−0.0666)
h_DLnFDI	0.00462	0.00372	−0.0196	−0.0857	0.0366	−0.0257*
	(−0.00635)	(−0.00352)	(−0.0161)	(−0.0821)	(−0.0355)	(−0.0146)
h_DLnTrade	−0.00396	−0.00221	0.0442*	0.00869	0.0136	0.0938***
	(−0.0105)	(−0.00683)	(−0.0264)	(−0.103)	(−0.079)	(−0.0342)
h_DLnIndusStruc	0.0640**	−0.0196	−0.143**	−0.784***	0.225	0.437***
	(−0.0255)	(−0.0171)	(−0.064)	(−0.236)	(−0.17)	(−0.0703)

5.3.3.2. Feedback effect. The feedback effect of CWED is reflected in the first column. The unexpected shock of CWED has a negative effect on the increase of FDI since the second year and decreases slightly in the next ten years. The shock of CWED has a small negative effect on the increase of trade, and fades out quite quickly in the first year. The trend of the response of fiscal expenditure growth is similar to that of industrial upgrade, except the effect is much smaller. The shock of CWED has a significantly positive effect on industrial upgrade and converges to zero slowly in the next ten years. The effect of CWED on expenditure growth only influences the CWED in the short-run. The effect of industry upgrade reaches its maximal point in the first year and then converges to zero in ten years. This indicates that the effect exists in the long-run. The direct effects of FDI and trade growth to CWED are not significant. However, the direct effect of FDI growth to industrial upgrade growth is negative and lasts for nearly ten years, as shown in the last row of Fig. 3. This suggests that FDI growth can have a negative effect on CWED indirectly through industry upgrade growth in the long-run. At last, foreign trade growth can have a short positive effect on CWED via fiscal expenditure growth and industry upgrade.

As shown in the second row of Fig. 3, except for *LnCWED* and energy structure, the other four variables have no significant effect on energy structure. Again, this result indicates that the primary energy consumption structure of China is dominated by coal and it needs quite a long time to change this situation. However, from the second column, we can find, except for CWED and industrial upgrade, the other four variables all have significant positive response when there is a shock from energy structure in the long-run. It can be interpreted that a province with a primary energy consumption endowment of higher coal share usually goes with a second sector leading economy due to its convenience to get resource. As we propose in the hypotheses, many economic factors, like FDI, trade and fiscal expenditure may be spurred by the energy-intensive industries and some of these factors may have positive effect on CWED. However, this indirect positive effect of higher degree of coal dominant energy consumption structure is weaker than the combined negative effects of the high level of carbon emission of coal and the impediment to the industrial upgrade.

energy structure change is not significant in the 95% confidential interval in the short-run, but the upper bound approaches zero as time progresses implying that low-carbon economic development tends to have a long-run influence on improving the energy structure. This result shows that the primary energy consumption structure requires a long time to be optimized.

6. Conclusion and policy implications

This paper contributes to the literature by proposing a novel Malmquist-Luenberger productivity (MPL) index termed as carbon weight economic development (CWED) based on directional slacks-based measure of technical inefficiency (DSBI) to address the issue of low-carbon economic evolution of DMUs in the presence of carbon emission and carbon sink. An extension of the computational framework for computing inefficiency is proposed to incorporate non-conventional inputs (needed to be expanded) and outputs (needed to be shrunk) in comparison to the traditional radial DEA method. The extended framework can solve the problem of slacks in the technological constraints while the standard DDF method may fail to do so. Comparing to the modified DSBI approach, the DDF method may underestimate the inefficiency.

We apply the framework to perform a case study over 30 provincial regions in China. The findings suggest that China experienced low-carbon economic development growth in the two periods of 1998–2002 and 2008–2014, while in the period of 2003–2007, CWED declined due to pursuing a high-speed GDP growth driven by energy intensive

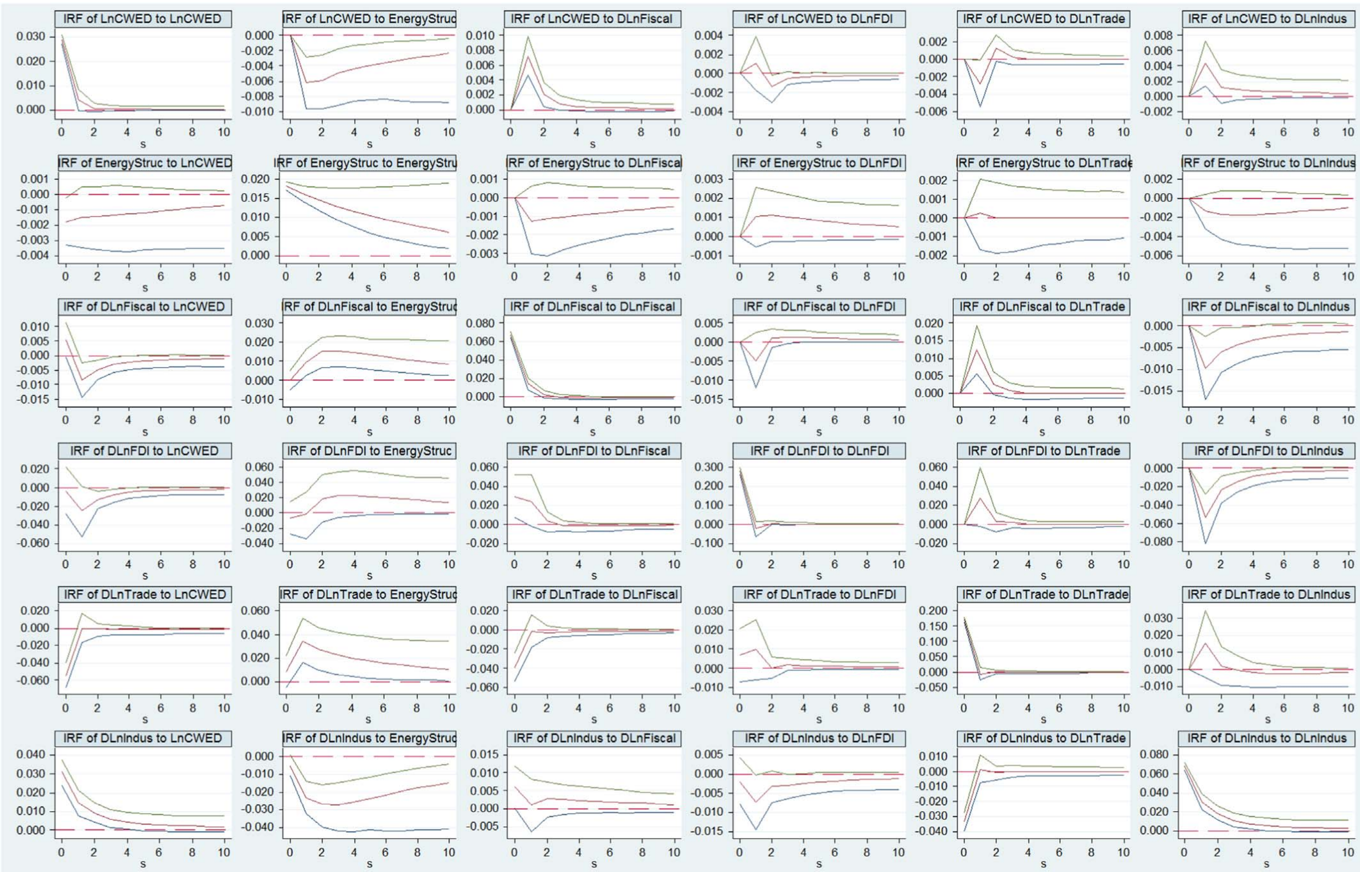

Fig. 3. Impulse response function of CWED to the six variables. Note: The six variables are ordered from top to bottom as: *LnCWEDP, EnergyStruc*, *DLnFiscal, DLnFDI,* and *DLnIndusStruc*; 500 times of Monte Carlo simulations are conducted. The center lines plot the estimates of the impulse response functions; the range between the upper- and -lower-line corresponds to the 95% confidence interval of the corresponding estimate.

industries. In addition, we employ a PVAR model to identify the driving forces behind low-carbon economic development in China. We find that (1) The ratio of coal in primary energy consumption has a negative effect on CWED both in the short-run and long-run. The growth of local fiscal expenditure has a positive effect on CWED only in the short-term. The growth associated with structural upgrade of industries positively effects CWED in both short-run and long-run. (2) The growth of FDI has a negative influence on CWED in the long-run through a negative effect on industrial structural upgrade. The growth of trade has a positive influence on CWED in the short-term through positive effects on local fiscal expenditure growth and industrial structural upgrade; (3) As for the feedback effect of CWED, developing low-carbon economy can benefit energy supply-consumption optimization and industrial upgrade in the long-run, but with a compromise of decreasing the FDI and fiscal expenditure growth. We combine all the results of PVAR(6) regression and impulse response function to determine the relationship between various variables, see Fig. 4.

The above findings lend important insights for governments to develop policies to improve low-carbon economic development. This study has four major policy implications. First, the proposed carbon-weighted economic development index is useful for policy-makers in various countries, not just China, to build a low carbon economic development performance evaluation system at regional level. This index and the empirical analysis can be generally applied to a broader setting where nations are regarded as DMUs. Second, to bolster its balanced economy, Chinese government shall focus more on filling the gap of low-carbon economic development performance between different regions, as the eastern region has been developing much faster than the central and western regions have. Such inequality partially comes from the historical gaps in the regional economies, but the trend of shifting energy-intensive industries from the east to the west and the central regions deserves thorough examination by the policy-makers. Different standards in energy efficiency and energy conservation target among regions would lead to carbon leakages. Third, the input-output analysis shows that energy efficiency improvements are still required. Supportive policies are needed for the development of energy conservation technologies and products, and the increase of the area of forest carbon sinks. Finally, to improve the low carbon economic development in the future, Chinese government shall further upgrade its industrial structure, adjust the energy consumption structure, and encourage foreign trade. As for FDI, the government needs to closely monitor it to avoid investments in carbon-emission intensive industry.

The National Development and Reform Commission of China recently released its policies and planned actions on climate change including five major measures as adjusting industrial structure, energy conservation and improving energy efficiency, optimizing the energy structure, controlling emission from non-energy activity and increasing carbon sinks. Our analysis provides empirical evidences in support of these measures, specifically by highlighting the impact of environmentally conscious upgrading of industrial structure on economic development. To elaborate on the fourth insight, we describe the pathway for low-carbon development of China. China is undergoing a process of economic restructuring and evolving into a post-industrialization stage characterized by a service-oriented economy by 2030. To become a low-carbon economy, upgrading the current industrial sectors by adopting low-carbon technology is a quicker approach than changing the fundamental structure of energy supply/consumption in both short and long-run. During this restructuring period, policy of vigorously boosting the transformation from the traditional energy-intensive manufacturing to energy-efficient service

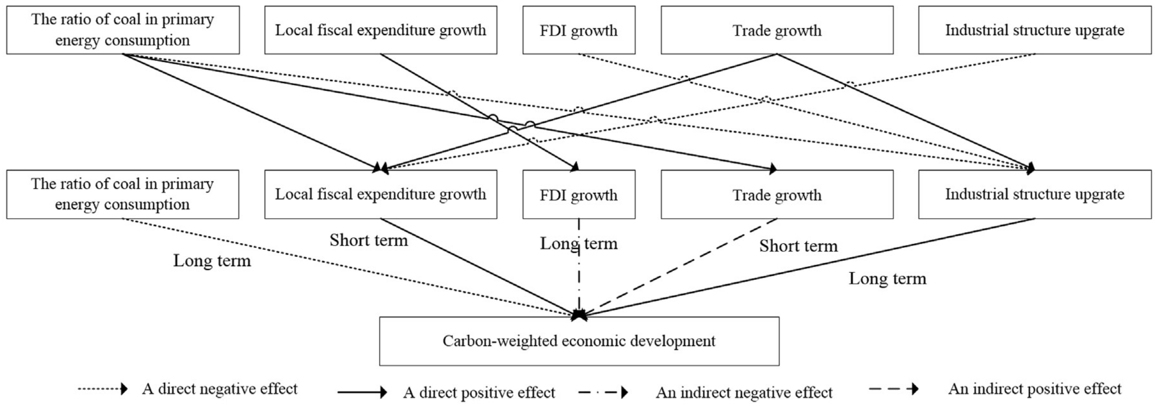

Fig. 4. The driving forces behind carbon-weighted economic development in China.

sector shall be formulated, together with the policy of eliminating outdated production capacity. Reducing the ratio of coal consumption to total primary energy consumption is the most effective way to promote low-carbon economy in both short-run and long-term. However, as coal, which is the primary energy supply source in China, accounts for more than 70% of the total energy consumption for decades, it is difficult to change the energy consumption structure in either the supply side or the demand side in a short period. In the long-term, as new technology of renewable energy develops, like wind, solar PV and tide, energy structure optimization would be easier to achieve with cleaner energy resources being made available. Coal consumption in China is reduced by 2.9% in 2014 compared to that in 2013 and this is the first time for China to have a decrease in coal consumption. This decrease may indicate the turning point of the driving factors for the low-carbon development of China. The energy structural optimization problem becomes more solvable than ever before.

As China has been in a rapid development for some time and accumulated considerable amount of resources and capital. At this stage of development, FDI flowing to the energy-intensive and environment-unfriendly sectors shall be held back to avoid the “Pollution Haven Hypothesis”. In the short-run, policy for fostering foreign trade can be beneficial for low-carbon economic development as foreign trades lead to expansion effect and technology transfer. Government expenditures on providing environment-related public goods and social welfare improvements need to be increased. Such expenditures include spending on environmental protection, R & D investments in energy conservation technologies and products, subsidies for developing renewables, financing of carbon sinks and grants in spreading information and education about low-carbon economy. In the short-run, these are effective ways to foster the low-carbon economic development.

While this study helps us better understand the low-carbon economic development and its driving forces, it has some limitations. First, the panel data collected for the studies has a limited time span. To capture more dynamic aspects of the economic impacts, it may require an extended dataset covering the period which dates back to the 1980s or even the 1970s. Also, the set of driving factors that may affect low-carbon economic development in China considered in this study is by no means complete. Alternative variables may play equally significant roles in affecting low carbon economic growth. For instance, the growth of the use of renewable energy is not included in this research due to the lack of data for the whole time period studied. Further research can improve the study by obtaining additional data and identifying additional variables that may impact the low-carbon economic development.

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