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ORIGINAL PAPER

Dynamic activity analysis model-based win-win development forecasting under environment regulations in China

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Abstract Porter hypothesis states that environmental regulation may lead to win-win opportunities, that is, improve the productivity and reduce the undesirable output simultaneously. Based on directional distance function, this paper proposes a novel dynamic activity analysis model to forecast the possibilities of win-win development in Chinese industry between 2011 and 2050. The consistent bootstrap estimation procedures are also developed for statistical inference of the point forecasts. The evidence reveals that the appropriate energy-saving and emission-abating regulation will significantly result in both the net growth of potential output and the increasing growth of total factor productivity for most industrial sectors in a statistical sense. This favors Porter hypothesis.

Keywords Dynamic activity analysis model · Win win development · Environmental regulations · China industry

1 Introduction

In the recent 20 years, the relationship among energy, environment and economy (3E) has always been a focal topic of scholars and policy makers. The traditional

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established notion on environmental protection is that the extra costs government imposes on the firms can jeopardize their international competitiveness. Porter, however, first challenged this argument in his one-page paper published in 1991 (Porter 1991). He regarded large energy consumption and pollutant emission as a form of economic waste and a sign of incompletion and inefficiency of resources using. In his opinion, the amelioration of this inefficiency will provide firms with the win-win opportunity of improving both the productivity and environment. And the efforts of environmental protection can help firms to identify and eliminate the production inefficiency and regulatory disincentives that prevent the simultaneous improvements in both productivity and environmental quality. Thus, whether these types of environmental policy initiatives are successful depends on the extent to which such inefficiencies are widespread in the sub-industries, particularly in the energy/pollution intensive industries. However, due to deficient management systems, firms are not aware of certain opportunities and that environmental policy might open the eyes. Porter and Linde (1995) further emphasized that properly designed environmental protection policy in the form of economic incentives can trigger innovation that may partially or fully offset the costs of complying with them. Such innovation offsets occur mainly because pollution regulation is often coincident with improved efficiency of resource usage and the inference is that stiffer environmental regulation results in greater productivity and competence. These arguments are titled as Porter hypothesis (Ambec and Barla 2002). Admittedly, many scholars criticize Porter hypothesis, arguing that it is a fundamental challenge to efficient market hypothesis and neoclassical theory, and if it does exist it will be unnecessary for the government to impose extra environmental protective costs on the firms. They question why firms do not see these win-win opportunities by themselves, which at least implies that the argument does not have a general validity (Palmer et al. 1995; Jaffe et al. 1995; Faucheux and Nicolaï 1998).

Empirical researches have provided arguments for both positions and have not been conclusive so far.[1] There are very rare studies to investigate the validness of Porter hypothesis in China, though it is critically important, too. Now China is the largest energy consumer and CO2 emitter in the world, which brings China much abatement pressure from the outside world. The limited energy resources and serious pollution emissions have also made the traditional growth model in China unsustainable. To transform the economic growth model and challenge the climate change, in 2009 China decided to abate the CO2 intensity by 40–45 % till 2020 as opposed to the benchmark level in 2005. Though it is only the relative carbon abatement, rather the absolute reduction employed by most countries, it is still challenging for China to realize it due to its coal oriented energy consumption structure and extensive factor-driving growth model. In particular, environment regulations will use up the limited resources which may be put into other productions and very likely influence the economic growth. Hence, an in-depth analysis is needed on both the positive and negative influence of

[1] Many empirical researches support Porter hypothesis, such as Karvonen (2001); Mohr (2002); Murty and Kumar (2003); Beaumont and Tinch (2004); Cerin (2006); Greaker (2006); Kuosmanen et al. (2009); Groom et al. (2010); Zhang and Choi (2013) There are also a few papers whose conclusion is neutral or against Porter hypothesis, see Boyd and McClelland (1999); Xepapadeas and Zeeuw (1999); Feichtinger et al. (2005).

environment regulations on China's economy, including the output and productivity growth. It is also a quite practical and edging issue to search for an optimal energy-saving and emission-abating path that can induce a win-win development for China in the following decades. Both motivate the research in this paper. As is known to all, on average, the industry counts for near 70 % of total energy consumption and over 80 % of the total CO2 emission in China, which makes it the primal target to save energy and abate emissions. However, China is currently in the middle stage of industrialization, in which energy and emission intensive sectors such as iron and steel, cement and chemistry industries will continue to play pivotal roles in future economic growth. Thus, we can foresee there will be more negative impact brought by energy-saving and emission-abating activities on China's industry. Therefore, this paper focuses on the win-win forecasting in China's industrial economy.

As denoted above, the empirical results on win-win development possibilities are conflicting, which may be due to different dataset for analysis, the regulatory regime in a country, different cultural setting, the customer behavior, the type of industries or size of companies to be analyzed, and the time span and so on. However, the main reason may be the lack of a reasonable theoretical framework within which to investigate the links between environmental regulation and economic performance (Schaltegger and Synnestvedt 2002). For example, the commonly used CGE model fits static analysis well but its dynamic extension in empirical study is still rather scarce and too simple. Parametric econometric model is restricted to its priori functional form and distribution assumption. Traditional data envelopment analysis (DEA) and Shepherd distance function cannot distinguish the different characteristics between desirable output like GDP and undesirable output such as pollutions. Not until the presence of directional distance function (DDF) do we find a reasonable framework to capture the difference between desirable and undesirable outputs, and to model the behavior of increasing desirable output while decreasing undesirable output simultaneously. DDF allows for the type of inefficiency that is typified by Porter hypothesis, providing the most appropriate approach to examine Porter hypothesis. By following Boyd et al. (2002), this paper makes use of two types of DDF based on the strong and weak disposability assumption of pollution emissions to measure the potential output gain and loss, and uses the standard DDF based Malmquist–Luenberger Productivity Index (MLPI) to forecast the change of total factor productivity (TFP) and its components. In order to forecast the win-win development possibility from now on to the year of 2050 and find the optimal environment regulatory path, this paper designs different energy-saving and emission-abating paths and proposes a new dynamic activity analysis model (AAM) in which the different paths are introduced into the direction vector of DDF to examine the influence of different regulation paths on the win-win development possibilities in China in the following 40 years. However, there clearly exists the uncertainty surrounding these forecasts due to sampling variation. It is not enough to know whether the forecasts indicate increases or decreases in efficiency and productivity, but whether the indicated changes are significant in a statistical sense. This paper develops a consistent bootstrap estimation procedure to obtain the confidence intervals for potential net output gain and the index of productivity and its decompositions. The bootstrap methodology is an extension of earlier work by Simar and Wilson (1998, 1999).

The rest of this paper is organized as below: Sect. 2 introduce the dynamic activity analysis model firstly proposed in this paper. How to measure the potential output gain and loss and the specification of the Malmquist–Luenberger productivity index are also illustrated in the section. Section 3 firstly designs different energy-saving and emission-abating paths, which will be added into the direction vector of DDF so as to extend the AAM into dynamic version. The section also designs the bootstrap procedure that allows us to make the distinctions between a real change in potential output and productivity and an artifact of sampling noise. Section 4 selects an optimal environment regulatory path for China's industrial win-win development during 2011 and 2050, and discusses the corresponding forecasts of potential output gain and loss, the evolution of productivity, technique and efficiency change among a set of sectors, and their statistical significance. Section 5 concludes this paper.

2 Dynamic activity analysis model

In the section, a novel dynamic activity analysis model (DAAM for short), not addressed so far, is proposed to forecast the effect of energy-saving and emission-abating regulations on economy in the long run, which is extended from the standard DDF-based AAM provided by Chambers et al. (1996) and Chung et al. (1997) and applied by Färe et al. (2001); Jeon and Sickles (2004) etc. How to simulate the potential output gain, output loss and the change of productivity, technique and efficiency by using the newly proposed DAAM approach is also introduced in the section. In the study, the decision-making units (DMU) are 38 two-digit industrial sectors ($i = 1, 2, \ldots, 38$). The forecasting time span is from 2011 to 2050 ($t = 2011, \ldots, 2050$). For each sector, there are three types of input ($j = 1, 2, 3$, corresponding to capital, labor and energy), one type of desirable output (gross industrial output value, GIOV), and one type of undesirable output (carbon dioxide emission, CO2). The historical dataset between 1980 and 2010 used for simulation is from Chen (2013). The panel data for 38 industrial sectors, rather than aggregate data, significantly enhances the information that could be obtained to analyze microeconomic performance, particularly when examining the efficiency of each unit.

For ith industrial sector, the column vectors of $\mathbf{x}^i$, $\mathbf{y}^i$ and $\mathbf{b}^i$ represent the inputs, desirable output and undesirable output, respectively. Then the production technology for ith sector at time point t can be described by its output set:

$$P\left(\mathbf{x}^i\right) = \left\{\left(\mathbf{y}^i, \mathbf{b}^i, -\mathbf{x}^i\right) : \mathbf{x}^i \; can \; produce \; \left(\mathbf{y}^i, \mathbf{b}^i\right)\right\} \tag{1}$$

Same as Shephard distance function, DDF is also the representative function to describe such a production technology. The principle of DDF is illustrated in Fig. 1. The technology is represented by the output set $P(\mathbf{x})$ to which the output vector of A point $(\mathbf{y}, \mathbf{b})$ belongs. Shephard's output distance function radially scales the original vector from point A proportionally to point D to describe the simultaneous increase of desirable and undesirable output. In contrast to this, the DDF starts at A and scales in the direction along ABC to capture the increase of desirable outputs (or goods) and decrease of undesirable outputs (or bads) simultaneously, which make it possible to

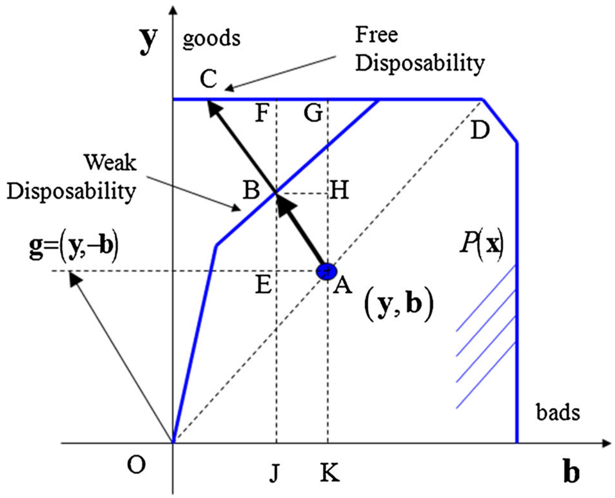

Fig. 1 Principle of directional output distance function

investigate Porter hypothesis that allow for the possibility of crediting units for the reduction of pollutions. Formally, DDF is defined as

$$\vec{D}_o\left(\mathbf{x}^i, \mathbf{y}^i, \mathbf{b}^i; \mathbf{g}^i\right) = \sup\left\{\beta : \left(\mathbf{y}^i, \mathbf{b}^i\right) + \beta\mathbf{g}^i \in P\left(\mathbf{x}^i\right)\right\} \tag{2}$$

where $\mathbf{g}$ is the direction vector in which outputs are scaled. In standard case, $\mathbf{g} = (\mathbf{y}, -\mathbf{b})$, as shown in Fig. 1. β is the maximum feasible expansion of the desirable outputs and contraction of the undesirable outputs when the expansion and contraction are identical proportions for a given level of inputs, which amounts to the value of DDF to be measured.

2.1 Production inefficiency and loss due to environmental regulation

As shown in Fig. 1, because the point A remains within the efficient production frontier, the inefficiencies resulted from such factors as wasteful energy consumption and serious pollution emissions give the producer the potential room to increase the output, given the inputs and current output, by saving energy and abating emission.[2] But whether the observation vector projects from the point A to point B or C depends on the weak or free disposal assumption of undesirable output. If assume that the undesirable output is strongly or freely disposal, that is, the disposability costs nothing, the producers will voluntarily get rid of the unwanted by-products, then the growth of potential output based on current desirable output will be maximized which amounts to the distance function value β_s (i.e., the ratio of AC/Og). In this case, energy and environment do not impose any restriction on output, then the production in point C is the most efficient. However, it's impossible to cost nothing to reduce undesirable output in reality. The producers therefore are not willing to reduce the undesirable

[2] In this case, the value of β is greater than zero which tell us the sizes of inefficiencies for the unit.

outputs because it makes use of the important inputs and then translates into the loss of desirable outputs given inputs. The reduction of undesirable outputs only can be achieved by environment regulations. Accordingly, the more appropriate assumption is weak disposability of undesirable output, the point A projecting into B on the frontier, which is the standard DDF, or referred to as environment regulatory AAM. Its value equals β_w or the ratio of AB/Og in the figure. In this case, the potential goods growth is a tradeoff between more goods and less bads, bound to below the maximized β_s under the strong disposability of bads.

The difference between β_w and β_s reflects the potential output loss caused by the observable lack of free disposability (more vividly, due to enforced environment regulations), i.e., $l = \beta_w - \beta_s < 0$ (Boyd et al. 2002). The value of l is analogous to the hyperbolic output loss measure introduced by Färe et al. (1989) and used by Boyd and McClelland (1999). The potential output loss l and potential output growth β_w reveal the extent of the win-win potential for each industrial sector, given current output at some time point. If potential β_w exceeds or equals the absolute value of l, $|l|$, from the perspective of output, the win-win opportunity due to environment regulations that is described by Porter hypothesis happens, to some extent suggesting that improved production efficiency can make up for the losses imposed by regulations. If $\beta_w < |l|$, it indicates that environmental regulations will not lead to the win-win development. This paper will make use of this method to find the best energy-saving and emission-abating path that leads to the win-win development potentials in China.

2.2 Dynamic activity analysis model (DAAM)

As stated previously, the direction vector in DDF is $\mathbf{g} = (\mathbf{y}, -\mathbf{b})$, and the value of DDF, β, captures the maximum feasible proportion that the goods $\mathbf{y}$ expand while the bads $\mathbf{b}$ contract based on current output level $(\mathbf{y}, \mathbf{b})$, the negative sign of $\mathbf{b}$ indicating the reduction of bads. To simulate the dynamic process of energy-saving and emission-reducing activity, in this paper, we introduce the time factor into the direction vector and redefine the output direction vector as $\mathbf{g}^t = \left(\mathbf{y}^t, -\mathbf{b}^t\right) = \left[(1+u)\,\mathbf{y}^{t-1}, -(1+v)\,\mathbf{b}^{t-1}\right]$, where u and v represent the changing rate of current industrial output (goods) and CO2 emissions (bads) relative to previous time point during the forecasting period, correspond to the different energy-saving and emission-abating paths to be designed in Sect. 3.1. Similarly, the dynamic changing path for the jth input vector is defined as $\mathbf{x}_j^t = \left(1+\sigma_j\right)\mathbf{x}_j^{t-1}$, where σ_j is the changing rate of the jth input to be discussed also in Sect. 3.1. In terms of the defined dynamic direction vector, the technology in t period and observation also in t period, the linear programming of two types of DDF, the assumption of weak and strong disposability of undesirable output, is specified respectively for ith sector as below.

Directional distance function (weakly disposable bads)

$$\vec{D}_o^t\left(\mathbf{x}^{i,t}, \mathbf{y}^{i,t}, \mathbf{b}^{i,t}; \mathbf{y}^{i,t}, -\mathbf{b}^{i,t}\right) = \underset{\lambda,\beta}{Max}\ \ \beta_w$$

$$s.t. \qquad \sum_{i=1}^{38} \lambda^i \mathbf{y}^{i,t} \geq (1+\beta_w)(1+u)\,\mathbf{y}^{i,t-1}$$

$$\sum_{i=1}^{38} \lambda^i \mathbf{b}^{i,t} = (1-\beta_w)(1+v)\,\mathbf{b}^{i,t-1}$$

$$\sum_{i=1}^{38} \lambda^i \mathbf{x}_j^{i,t} \le \left(1+\sigma_j\right)\mathbf{x}_j^{i,t-1} \quad (j=1,2,3)$$

$$\beta, \lambda^i \ge 0 \quad (i=1,2,\ldots,38) \tag{3}$$

In linear programming (3), $\beta = 0$ means that the industrial sector lies on the possibility frontier and its production is efficient; while $\beta > 0$ implies that the sector is inefficient in production. The proportion of the sectors with $\beta > 0$ to all sectors shows us how widespread the inefficiencies are in the industry, which is related to the win-win opportunities by environmental regulation. The inequality for goods in (3) makes it freely disposable which means that the goods can be disposed of without the use of any inputs and then without the decrease of bads. The bads is modelled with equality that makes it weakly disposable. The inequality specification of inputs illustrates also that the inputs are strongly disposable; that is, the increase of inputs will not cause the decrease of output. The intensity variable λ^i is the weight assigned to each sector when constructing the production frontier. As shown in linear programming (3), novel definition of dynamic output and input direction vector not only introduces many possible energy-saving and emission-abating paths into DDF in order to capture the regulatory behavior but also makes it possible to forecast the dynamic impact of energy-saving and emission-abating activity on economy in the following decades. Therefore, we abuse terminology and refer to the extended DDF as dynamic (environmental regulatory) activity analysis model (DAAM), which distinguishes itself from the standard DDF and AAM in that it has introduced the time lag operator into the direction vector.

Directional distance function (strongly disposable bads)

$$\vec{D}_o^t\left(\mathbf{x}^{i,t}, \mathbf{y}^{i,t}, \mathbf{b}^{i,t}; \mathbf{y}^{i,t}, -\mathbf{b}^{i,t}\right) = \underset{\lambda,\beta}{Max}\ \beta_s$$

$$s.t. \qquad \sum_{i=1}^{38} \lambda^i \mathbf{y}^{i,t} \ge (1+\beta_s)(1+u)\,\mathbf{y}^{i,t-1}$$

$$\sum_{i=1}^{38} \lambda^i \mathbf{b}^{i,t} \ge (1-\beta_s)(1+v)\,\mathbf{b}^{i,t-1}$$

$$\sum_{i=1}^{38} \lambda^i \mathbf{x}_j^{i,t} \le \left(1+\sigma_j\right)\mathbf{x}_j^{i,t-1} \quad (j=1,2,3)$$

$$\beta, \lambda^i \ge 0 \quad (i=1,2,\ldots,38) \tag{4}$$

From the mathematical perspective, the equality constraint of undesirable output in linear programming (3) is changed into the same inequality constraint as on the desirable output to reveal the strong disposability of undesirable output in linear programming

(4). As mentioned above, the difference of solutions between (3) and (4) measures the potential production loss due to energy-saving and emission-reducing activity.

2.3 Malmquist–Luenberger Productivity Index (MLPI)

The DAAM approach summarized in linear programming (3) with the weak disposal assumption of undesirable output models the energy-saving and emission-abating activity; therefore, it can be used to measure the change of total factor productivity (TFP) and its decomposition under environmental regulations by calculating the Malmquist–Luenberger Productivity Index (MLPI). To the end, four different types of DDF must be solved for each sector: two use observations and technology at time period t and $t+1$, $\vec{D}_o^t\left(\mathbf{x}^{i,t}, \mathbf{y}^{i,t}, \mathbf{b}^{i,t}; \mathbf{y}^{i,t}, -\mathbf{b}^{i,t}\right)$ and $\vec{D}_o^{t+1}\left(\mathbf{x}^{i,t+1}, \mathbf{y}^{i,t+1}, \mathbf{b}^{i,t+1}; \mathbf{y}^{i,t+1}, -\mathbf{b}^{i,t+1}\right)$; and two use adjacent period, for example, $\vec{D}_o^t\left(\mathbf{x}^{i,t+1}, \mathbf{y}^{i,t+1}, \mathbf{b}^{i,t+1}; \mathbf{y}^{i,t+1}, -\mathbf{b}^{i,t+1}\right)$ calculated from t period technology with the $t+1$ period observation, and $\vec{D}_o^{t+1}\left(\mathbf{x}^{i,t}, \mathbf{y}^{i,t}, \mathbf{b}^{i,t}; \mathbf{y}^{i,t}, -\mathbf{b}^{i,t}\right)$ calculated from $t+1$ period technology with the t period observation. Then the Malmquist–Luenberger Productivity Index (MLPI) defined by Chung et al. (1997) can be computed using the following formulas:

$$MLPI^{t,t+1} = \left[\frac{1+\vec{D}_o^t\left(\mathbf{x}^{i,t}, \mathbf{y}^{i,t}, \mathbf{b}^{i,t}; \mathbf{y}^{i,t}, -\mathbf{b}^{i,t}\right)}{1+\vec{D}_o^t\left(\mathbf{x}^{i,t+1}, \mathbf{y}^{i,t+1}, \mathbf{b}^{i,t+1}; \mathbf{y}^{i,t+1}, -\mathbf{b}^{i,t+1}\right)} \times \frac{1+\vec{D}_o^{t+1}\left(\mathbf{x}^{i,t}, \mathbf{y}^{i,t}, \mathbf{b}^{i,t}; \mathbf{y}^{i,t}, -\mathbf{b}^{i,t}\right)}{1+\vec{D}_o^{t+1}\left(\mathbf{x}^{i,t+1}, \mathbf{y}^{i,t+1}, \mathbf{b}^{i,t+1}; \mathbf{y}^{i,t+1}, -\mathbf{b}^{i,t+1}\right)}\right]^{1/2} \tag{5}$$

The Malmquist–Luenberger index is the most widely used productivity index and is particularly attractive when constructing it since it does not rely on prices, particularly the price of CO2 appeared in this study. The MLPI can be decomposed as the product of two terms: the index of Malmquist–Luenberger technical change (MLTCH) and Malmquist–Luenberger efficiency change (MLECH); that is

$$MLPI^{t,t+1} = MLTCH^{t,t+1} \cdot MLECH^{t,t+1} \tag{6}$$

where,

$$MLTCH^{t,t+1} = \left(\frac{1+\vec{D}_o^{t+1}\left(\mathbf{x}^{i,t+1}, \mathbf{y}^{i,t+1}, \mathbf{b}^{i,t+1}; \mathbf{y}^{i,t+1}, -\mathbf{b}^{i,t+1}\right)}{1+\vec{D}_o^t\left(\mathbf{x}^{i,t+1}, \mathbf{y}^{i,t+1}, \mathbf{b}^{i,t+1}; \mathbf{y}^{i,t+1}, -\mathbf{b}^{i,t+1}\right)} \cdot \frac{1+\vec{D}_o^{t+1}\left(\mathbf{x}^{i,t}, \mathbf{y}^{i,t}, \mathbf{b}^{i,t}; \mathbf{y}^{i,t}, -\mathbf{b}^{i,t}\right)}{1+\vec{D}_o^t\left(\mathbf{x}^{i,t}, \mathbf{y}^{i,t}, \mathbf{b}^{i,t}; \mathbf{y}^{i,t}, -\mathbf{b}^{i,t}\right)}\right)^{1/2} \tag{7}$$

$$MLECH^{t,t+1} = \frac{1+\vec{D}_o^t\left(\mathbf{x}^{i,t}, \mathbf{y}^{i,t}, \mathbf{b}^{i,t}; \mathbf{y}^{i,t}, -\mathbf{b}^{i,t}\right)}{1+\vec{D}_o^{t+1}\left(\mathbf{x}^{i,t+1}, \mathbf{y}^{i,t+1}, \mathbf{b}^{i,t+1}; \mathbf{y}^{i,t+1}, -\mathbf{b}^{i,t+1}\right)} \tag{8}$$

If $MLPI > 1$, it means that TFP grows over the adjacent period; while $MLPI < 1$ indicates that TFP declines.

3 Forecasting scheme

3.1 Design energy-saving and emission-abating paths

Different energy-saving and emission-abating paths will have obviously different impact on economy (Lee et al. 2007; Kuosmanen et al. 2009). This paper designs three energy-saving scenarios and seven emission-reducing scenarios, totally twenty one combinations of environment regulatory paths. By introducing different regulatory paths into the DAAM approach proposed in Sect. 2.2, this paper will forecast their effect on the potential growth of output and productivity in the following four decades so as to look for the best regulatory path leading to a win-win development possibility for Chinese industry.

Before the design of changing paths of energy and emission, we firstly specify the changing patterns for industrial output and other inputs such as capital stock and labor in the future. According to Chen and Golley (2014), between 1981 and 2010 the historical average growth rate of total industry is about 12.6, 9.3 and 2.6 % for output, capital and labor, respectively. Their growth rates in 2010 are 20.4, 14.1 and 5.3 %, higher than their historical average growth. However, after 30 years of rapid economic growth since the reform in 1978, China is facing a long-term decline in its economic growth rate, given its latest records. Thus, we assume that the growth rate of output, capital and labor will decreases from their respective growth rate in 2010 evenly to one third of their historical average growth in 2050 for each industrial sector and the aggregate industry. The design of energy saving scheme is based on the promissory targets to save energy stipulated by China government. Specifically, China central government promise to decrease the energy consumption per unit of output (i.e., energy intensity) by 20 and 16 %, respectively, during the period of 11st and 12nd five-year-plan, translating into 4.36 and 3.43 % annual reducing rate of energy intensity. In fact, during the 11st five-year-plan period, China decreased the energy intensity by 19%, 1% below the target rate. Therefore, this paper designs three scenarios for energy save; that is, the energy intensity will decrease by 3, 4, 5 % per year in the following 40 years. According to the annual growth rate of industrial output specified already, this can be translated into three paths of energy save between 2011 and 2050.

This paper designs the emission abatement scheme according to two specification of relative and absolute abatement, the former of which caters to the state condition that China is a developing country whose major task is to develop. If output experiences a rapid growth, CO2 emission may have a not low growth, too. As mentioned in introduction part, China officially announced that it will abate the CO2 intensity by 40–45 % in 2020 as opposed to the intensity in 2005. That means China should decrease the CO2 intensity by 3.4–3.9 % per year during that period. During the period of 12nd five-year-plan, China plans to reduce the CO2 intensity by 17 %, i.e. 3.66 % per year. Based on this, we will design three scenarios for CO2 relative abatement;

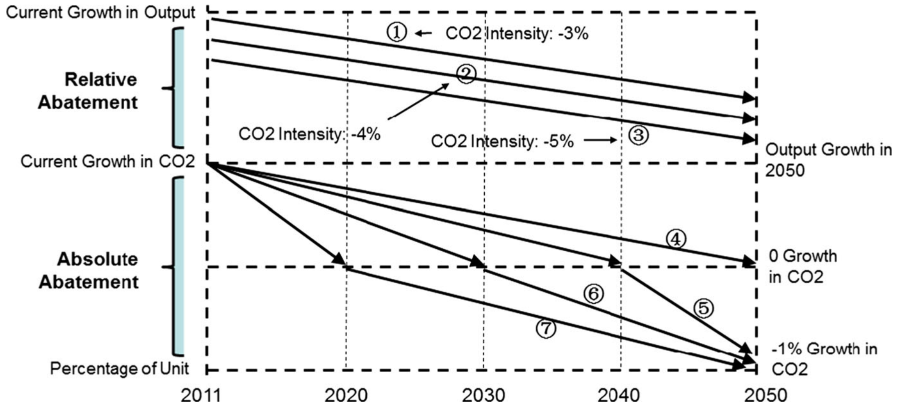

Fig. 2 Carbon dioxide abatement paths (1–7) for Chinese industry (2011–2050)

that is, CO2 intensity will decrease annually by 3, 4 and 5 %, respectively. As depicted in Fig. 2, given specified declining growth of industrial output, this will also leads to three decreasing emission paths (1–3 path). Most countries adopt the strategy of absolute abatement of CO2 emissions. As illustrated in Fig. 2, this paper designs four scenarios for absolute abatement, which is attributable to the generalized understanding of emission abatement concept that emission reduction does not necessarily refers to the absolute decline in emission level; a declining emission growth rate or declining relative to BaU is also a type of emission abatement. Specifically, four scenarios include: (1) the growth rate of CO2 for different sectors decreases from their respective growth in 2010 evenly to zero growth in 2050 (that is, the emission peak will appear in mid of this century); (2) the emission growth of all sectors reduces from the growth rate in 2010 to zero growth in 2039 and, after the emission peak, continuously decreases to $-1\,\%$ growth rate in 2050; the 3rd and 4th path are similar to the 2nd path but the emission peak is moved on to the year of 2030 and 2020, respectively. The twenty one energy-saving and emission-abating paths, together with the varying paths of industrial output, capital and labor, will be introduced into the dynamic activity analytical model (DAAM) mainly through direction vector so as to forecast the effect of environment regulations on output and productivity in the following decades.

3.2 Bootstrapping potential output gain, productivity change and its components

Lovell (1993) have labeled the nonparametric DEA and its variants as the deterministic approaches, which seems to suggest that they do not have statistical underpinnings and are sensitive to the sampling variations. Since the pioneering work by Efron (1979) and its extensions in the frontier framework by Hall et al. (1995), the bootstrap methodology is often used to undertake the statistical inferences on distance function of DEA approach. The key to obtaining consistent bootstrap estimates of distance function lies in consistent replication of the data generating process. Simar and Wilson (1998) argued that resampling from the empirical distribution of the data (i.e., drawing with replacement from the set of original distance function estimates) will lead to inconsistent bootstrap estimation. They proposed the smooth bootstrap to overcome this problem and yield consistent estimates of distance function. Simar and Wilson (1999) applied the principle to bootstrap the Malmquist productivity index. Following this, this paper extends the ideas to directional distance function and the Malmquist–Luenberger productivity index and its components.

Bootstrapping the distance function specified in the linear programming (3) is firstly exemplified. Its complete bootstrap algorithm could be summarized by the following steps:

1) By using the linear programming (3), compute $\{\beta_w^k,\ k = 1,\ 2,\ \ldots,\ n\}$;
2) Define the empirical distribution function for efficiency scores by putting mass $\frac{1}{n}$ on $\beta_w^i,\quad i = 1,\ 2,\ \ldots,\ n$;
3) By using the univariate kernel density estimator and the reflection method described in Simar and Wilson (1998), generate a random sample $\{\beta_{w,b}^{i*},\ i = 1,\ 2,\ \ldots,\ n\}$ [3] from the empirical distribution function defined in 2);
4) Compute the pseudo-sample $\left\{\left(\mathbf{x}^i, \mathbf{y}_b^{i*}, \mathbf{b}_b^{i*}\right),\ i = 1, 2, \ldots, n\right\}$, where $\mathbf{y}_b^{i*} = \mathbf{y}^i\ \left(1 + \beta_w^i\right)/\left(1 + \beta_{w,b}^{i*}\right)$ and $\mathbf{b}_b^{i*} = \mathbf{b}^i\ \left(1 - \beta_w^i\right)/\left(1 - \beta_{w,b}^{i*}\right)$;
5) By using the pseudo-sample produced in 4) and the linear programming (3), compute the bootstrap estimate of $\beta_w^k : \{\beta_{w,b}^{k*},\ k = 1,\ 2,\ \ldots,\ n\}$
6) Repeat 3)-5) B times to obtain a set of estimates

$$\{\beta_{w,b}^{k*},\ k = 1,\ 2,\ \ldots,\ n,\ b = 1,\ \ldots,\ B\}$$

In this study, n = 38, B = 2,000, and h = 0.02.[4]

Bootstrapping for the distance function β_f specified in the linear programming (4) in this study largely involves a straightforward translation of the notation in above steps. Once the bootstrap values have been computed, we can construct the confidence intervals of the distance function and its linear combinations at the desired level of significance.

The methodology for bootstrapping distance function in linear programming (3) and (4) could be easily adapted to the productivity index, except that the time-dependence structure of the panel data must be taken into account. According to formulas (5)–(8), we firstly obtain the point forecasts of Malmquist–

[3] The random sample is generated according to

$$\beta_{w,b}^{i*} = \begin{cases} \beta_{w,b}^{i,0*} + h\varepsilon_b^{i*} & if\ \beta_{w,b}^{i,0*} + h\varepsilon_b^{i*} \leq 1 \\ 2 - \beta_{w,b}^{i,0*} - h\varepsilon_b^{i*} & otherwise \end{cases}$$

where $\left\{\beta_{w,b}^{i,0*}, i = 1, 2, \ldots, n\right\}$ is a simple bootstrap sample from $\left\{\beta_w^i, i = 1, 2, \ldots, n\right\}$, that is, obtained by drawing with replacement from $\left\{\beta_w^i, i = 1, 2, \ldots, n\right\}$, ε_b^{i*} is a random drawn from a standard normal, and h is the smoothing parameter of bandwidth.

[4] As Daraio and Simar (2007) denoted, B should be greater than 2,000. The choice of kernel bandwidth controls the smoothness of the probability density curve. Following Simar and Wilson (1998), we choose h = 0.02 in this paper which provides a reasonably smooth estimate of the distribution function of efficiency scores.

Luenberger productivity index and its components in adjacent period of t_1 and t_2, $\{(MLPI^{k,t_1,t_2}, MLTCH^{k,t_1,t_2}, MLECH^{k,t_1,t_2}), k = 1, 2, \ldots, n\}$. To bootstrap the productivity index and its components, we need the data in adjacent time periods to consider the possibility of temporal correlation. To preserve any temporal correlation present in the data, following Simar and Wilson (1999), we make use of bivariate kernel density estimator and reflection method to generate two joint random samples of $\left\{\beta_{w,b}^{i,t_1,*}\right\}$ and $\left\{\beta_{w,b}^{i,t_2,*}\right\}$ $i = 1, \ldots, n$, and then compute two adjacent pseudo-samples of $\left\{\mathbf{x}^{i,t_1}, \mathbf{y}_b^{i,t_1,*}, \mathbf{b}_b^{i,t_1,*}\right\}$ and $\left\{\mathbf{x}^{i,t_2}, \mathbf{y}_b^{i,t_2,*}, \mathbf{b}_b^{i,t_2,*}\right\}$ $i = 1, 2, \ldots, n$. Based on two pseudo-samples and formulas (5)–(8), we could compute one bootstrap estimate of Malmquist–Luenberger productivity index and its components of technical and efficiency change. This step will be repeated for B times to provide a set of estimate of $\left\{\left(MLPI_b^{k,t_1,t_2,*}, MLTCH_b^{k,t_1,t_2,*}, MLECH_b^{k,t_1,t_2,*}\right), k=1, 2, \ldots, n, b=1, \ldots, B\right\}$. Likely, in this paper, n = 38, B = 2,000, and the smoothing parameter for bivariate bivariate normal kernel $h = (4/5n)^{1/6}$.[5] The bootstrapping values of *MLPI*, *MLTCH* and *MLECH* could be used to test if there is a real change in productivity, technique and efficiency in the following 40 years from a statistical perspective.

4 Forecasting analysis

4.1 Simulate the win-win prospect under different environment regulatory paths

Table 1 reports the potential industrial output growth β_w, output loss l and corresponding net output gain averaged over the entire forecasting period under twenty one environmental regulatory paths combined by three energy-saving scenarios and seven emission-reducing scenarios.

As shown in Table 1, the former three emission abating paths are designed in terms of CO2 intensity reduction targets and classified into the relative abatement group and the latter four paths into the absolute abating group. On the whole, considering the fact of priority in development for China, seven emission abating paths specified in both groups are modest. On average, the abating path 1 in relative abatement group will not lead to the emission inflexion during entire forecasting period, while the emission peak appear in 2050 and 2048 for abating path 2 and 3, similar to the case in path 4 in absolute abating group, indicating that the emission abatement specified in relative abatement group is more modest than that in absolute group. Mostly, the distribution of the values of potential output growth, output loss and net gain display a quite regular varying pattern as shown in the table. For three energy saving paths, the potential output growth increases as the abating rate of emission intensity increases from 3 to 5 % (path 1–path 3); for first two energy saving paths, the potential output growth increases first and then turns to fall from abatement path 4 to path 7, and, corresponding to third energy saving path, the potential output growth always increases in the absolute abatement group. For three energy saving paths, the potential output loss exhibit a consistently deterioration

[5] Silverman (1978, 1986) and Härdle (1990) discuss considerations relevant to the choice of h. In the paper, we use Silverman (1986) suggestion for h setting since we are using a bivariate normal kernel.

Table 1 Potential output gain-loss analysis corresponding to 21 energy-saving and emission-abating paths (%)

Energy saving and emission abating paths	Relative abatement			Absolute abatement			
	Path 1 Emission intensity, 3 %	Path 2 Emission intensity, 4 %	Path 3 Emission intensity, 5 %	Path 4 Emission peak in 2050	Path 5 Emission peak in 2040	Path 6 Emission peak in 2030	Path 7 Emission peak in 2020
Energy intensity, 3 %							
βW	17.43	18.27	18.98	17.73	18.40	17.74	16.60
$l = \beta W - \beta f$	−23.64	−23.74	−24.35	−24.76	−25.41	−26.04	−26.09
Net gain	−5.50	−5.47	−5.60	−5.80	−5.94	−6.16	−6.25
Energy intensity, 4 %							
βW	19.21	19.48	20.23	17.18	18.91	18.70	17.88
$l = \beta W - \beta f$	−26.50	−26.67	−26.89	−26.67	−27.20	−29.70	−30.29
Net gain	−6.19	−6.22	−6.23	−6.37	−6.41	−7.13	−7.35
Energy intensity, 5 %							
βW	17.62	18.99	20.19	17.60	17.81	18.57	18.73
$l = \beta W - \beta f$	−30.44	−32.43	−32.98	−33.43	−33.72	−34.71	−35.04
Net gain	−7.41	−7.88	−7.95	−8.26	−8.33	−8.56	−8.64

from the emission abating path 1 to path 7, except the value of −26.89 and −26.67 % in path 3 and path 4 in the second energy path. Accordingly, the averaging net output gain also consistently increases from emission abating path 1 to path 7 no matter what kind of scenario for the energy save (with one exception of −5.50 % in first path of both energy save and emission abatement), implying that the optimal energy-saving and emission-abating path must be in the relative abating group. From the dimension of energy save, with the increasing of intensity of energy save the potential output growth does not exhibit a regular changing pattern but the potential output loss does experience the deteriorating process for all the seven emission abating paths, leading to a similarly deteriorating net output gain for all the abating scenarios. It is thus clear that appropriately decreasing the intensity of energy save will reduce the widespread extent of production inefficiencies, leading to the shrinking of improving space for potential output growth. Taken together, on average, the lowest potential net output gain is −5.47 %, appearing in the combination of first energy saving path and second emission abating path in relative abatement group. This is the optimal energy-saving and emission abating path we select for further investigation next; that is, according the scenarios simulation, the optimal environment regulatory path is to decrease the energy intensity by 3 % per year and decrease the CO_2 emission intensity by 4 % per year in the following 40 years. Since all the potential net gain shown in Table 1 are negative, it seems that all paths cannot lead to the win-win development suggested by Porter hypothesis, even though the best energy-saving and emission-abating path chosen above.

The findings in Table 1 are consistent with most other researches. Schaltegger and Synnestvedt (2002) argue that not merely the level of environmental performance, but mainly the kind of environmental management approach with which a certain level is achieved, influences the economic outcome, thus, the economic success resulted from the environmental protection finally depends on the chosen kind of regulatory approach rather the level. It's suggestion that research and business practice should focus more on the effect of different environmental management approaches on economic performance is consistent with the methodology used in our studies. Roughgarden and Schneider (1999) use a dynamic integrated climate-economy model to calculate an optimal rate of carbon tax and suggest that an efficient policy for slowing global warming would incorporate only a relatively modest amount of abatement of greenhouse gas emissions, via the mechanism of a small carbon tax. Chen et al. (2004) find that the earlier the emission reducing policy is implemented the greater the GDP loss will be. If the start of the emission reductions is the year of 2030, 2020 or 2010 instead of 2040, then the undiscounted total GDP losses in the whole planning horizon would be 0.58–0.74, 1.00–1.32, or 1.10–1.83 times higher. Kuosmanen et al. (2009) suggest that if one is only interested in greenhouse gases abatement at the lowest economic cost, then equal reduction of emissions over time is preferred. These researches all support the strategy of gradual and modest emission abatement. Similar to the idea of our paper that there is a close relationship between emission reduction and development, Reddy and Assenza (2009) also suggest that the integration of climate policies with those of development priorities that are vitally important for developing countries and stress the need for using sustainable development as a framework for climate change policies.

4.2 The influence of environment regulation on future potential output

Murty and Kumar (2003) pointed out that the win-win opportunities under the environmental regulations could be found more in some industries and less in others, and the studies for specific industries could help us to identify the industries with no such opportunities so that the monitoring and enforcement could be directed to those industries in which incentives are absent. As a matter of fact, it is also the reason why we focus on the analysis of China's industrial sectors instead of merely the aggregated industry. Therefore, under the optimal path of energy save and emission reduction chosen in previous subsection, this subsection further simulates the potential output growth, output loss and net output gain for all sectors in the following 40 years. Table 2 illustrates the forecasting prospects for each sector in the first forecasting year 2011, the win-win turning year and the last forecasting year of 2050 with the bootstrapping confidence interval for the net output gain. Specifically, the second and third column contains the original estimate of β_w and output loss of $l = \beta_w - \beta_f$ in 2011; the following three columns show the win-win turning year in which the potential output growth exceeds the output loss firstly in the forecasting period; the potential output gain, output loss, net gain and its confidence interval in 2050 are reported after the win-win information.

Table 1 has shown that the averaged net output gains brought by different regulatory paths are all negative, even though by the best energy-saving and emission-abating

Table 2 Sectoral output gain and loss in 2011, win-win turning year and 2050

Forecasting period	First year (2011)		Win-win turning point			Last year(2050)				
Sectors	βw	$l = \beta w - \beta f$	Year	βw	$l = \beta w - \beta f$	βW	$l = \beta w - \beta f$	Net Gain	Confidence Interval	
									Lower limit	Upper limit
Coal	19.87	−69.29	2025	19.50	−18.11	19.02	−0.57	18.45	16.48	20.41
Petroleum Ext.	9.96	−595.28	*not exist*			8.62	−30.56	−21.94	−23.94	−19.93
Ferrous Mi.	9.90	−590.76	*not exist*			9.27	−71.50	−62.23	−64.19	−60.27
Non-ferrous Mi.	33.89	−79.31	2038	9.66	−8.88	9.45	−7.50	1.96	0.01	3.90
Nonmetal Mi.	44.82	−198.94	2040	18.04	−16.95	14.79	−1.58	13.21	11.26	15.16
Wood Exp	69.98	−476.20	2045	22.92	−22.56	22.91	−7.81	15.10	13.16	17.03
Food Prod.	99.87	−179.99	2039	53.61	−50.75	53.41	−27.36	26.05	24.08	28.02
Food Ma.	129.92	−224.26	2030	35.88	−33.80	15.71	−5.03	10.68	8.70	12.66
Beverage	79.92	−166.50	2017	75.87	−70.61	17.65	−3.97	13.68	11.68	15.68
Tobacco	9.67	−68.80	2028	9.12	−7.95	2.15	0.00	2.14	0.19	4.10
Textile	109.93	−244.45	2031	47.64	−45.37	28.56	−18.36	10.20	8.24	12.15
Apparel	26.70	−80.93	*not exist*			18.59	−25.22	−6.63	−8.55	−4.72
Leather	69.62	−91.67	*not exist*			28.27	−30.15	−1.88	−3.84	0.07
Wood Prod.	39.85	−123.07	2048	29.09	−29.09	29.12	−28.71	0.41	−1.56	2.37
Furniture	9.18	−59.79	2035	7.07	−7.02	5.53	−3.51	2.01	0.02	4.01
Paper	39.96	−112.10	2035	29.58	−27.57	28.89	−1.74	27.15	25.25	29.05
Printing	68.89	−146.57	*not exist*			32.55	−41.85	−9.30	−11.20	−7.40
Cultural articles	39.01	−76.96	2043	36.78	−35.52	35.94	−25.96	9.97	7.98	11.96
Petroleum Prod.	140.00	−303.60	2016	100.00	−98.27	50.97	−0.43	50.53	48.58	52.49
Chemical products	73.60	−99.15	2019	58.93	−55.06	37.07	−11.69	25.38	23.39	27.36
Medicine	99.24	−49.84	From2011			20.84	−9.30	11.54	9.56	13.53

Table 2 continued

Forecasting period	First year (2011)		Win-win turning point			Last year(2050)				
Sectors	βw	$l = \beta w - \beta f$	Year	βw	$l = \beta w - \beta f$	βW	$l = \beta w - \beta f$	Net Gain	Confidence Interval	
									Lower limit	Upper limit
Fibers	149.84	−212.87	2037	66.69	−66.60	66.18	−43.15	23.04	21.07	25.00
Rubber	141.84	−232.07	2031	98.44	−97.87	65.68	−39.09	26.59	24.68	28.51
Plastic	39.07	−139.72	*not exist*			26.36	−31.50	−5.13	−7.13	−3.13
Nonmetal Ma.	29.34	−73.62	2019	28.58	−27.36	26.97	−0.31	26.66	24.69	28.62
Ferrous press	120.11	−131.42	2034	109.09	−106.67	102.78	−4.83	97.95	96.03	99.86
Non-ferrous press	139.71	−176.34	2030	128.71	−128.55	117.44	−31.85	85.59	83.62	87.56
Metal products	96.89	−164.72	2043	32.58	−32.43	32.56	−16.18	16.38	14.42	18.35
General machinery	9.57	−105.30	2041	1.10	−0.90	1.04	−0.01	1.04	−0.92	2.99
Special machinery	9.81	−94.50	2029	9.23	−6.61	1.40	−0.02	1.38	−0.58	3.34
Transport equipment	9.63	−63.28	2025	8.57	−7.85	0.33	−0.04	0.29	−1.72	2.29
Electrical equipment	29.51	−40.09	2028	8.61	−7.96	6.12	−0.33	5.80	3.81	7.78
Computer	16.62	−11.58	From2011			3.30	−0.01	3.30	1.34	5.25
Measuring instrument	8.24	−36.78	2035	2.06	−1.49	1.74	−0.12	1.63	−0.30	3.55
Electric power	79.92	−141.96	2018	56.87	−55.86	9.99	−0.98	9.00	7.04	10.96
Gas Prod.	19.99	−178.93	2037	9.99	−7.43	9.83	−1.75	8.07	6.10	10.04
Water Prod.	49.87	−70.49	2029	49.52	−49.37	45.36	−26.05	19.31	17.42	21.19
Others	49.87	−142.61	2037	8.57	−8.45	5.36	−4.18	1.18	−0.78	3.13

path. However, if we look at the simulation results for 38 industrial sectors reported in Table 2 rather the aggregated industry only, the situation will be totally another story. Overall, the potential output loss exhibits an obviously declining trend for all sectors and the potential output growth of most sectors has a modest decline or does not change much. Except for six sectors such as extraction of petroleum and natural gas, mining and processing of ferrous metal ores, apparel manufacturing, leather manufacturing, printing, and plastic manufacturing, the potential output loss for all the other sectors appears to be smaller than potential output growth at some time point before 2050. Table 2 has listed the respective turning year for the remaining sectors in which the potential output growth exceeds the output loss firstly in the entire forecasting period. Note that two sectors such as medicine manufacturing and manufacture of computers, communication equipment and other electronic equipment have higher output growth than output loss even from the first forecasting year of 2011. This indicates that for most sectors, the energy-saving and emission-abating activity can bring the win-win development opportunity in the forecasting period. Even to the above exceptional six sectors, their potential output losses tend to decline, too, and are bound to be lower than the potential growth at certain time after the year of 2050, leading to an expected win-win development.

The reason why the averaged net gain for all paths, even the optimal path, is negative in Table 1 is that most sectors have large potential loss in the nearer future, as shown in Table 2. It is thus clear that the aggregation analysis is undependable and even leads you to the opposite conclusion. Particularly, the potential output loss of those energy and emission intensive sectors such as extraction of petroleum and natural gas, mining and processing of ferrous metal ores, exploiting of wood and bamboo, processing of petroleum and coking are extremely large, which should be one of the causes of the negative weighted potential net gain for aggregated industry. Moreover, what we care about the energy save and emission reduction is its final influential level instead of accumulative effect; hence, the high potential output loss in the nearer future is just meaningful for that period and useless for the analysis on the future opportunity of win-win development. The last three columns in Table 2 report the net output gain $\beta_w - l = 2\beta_w - \beta_f$ in the last forecasting year of 2050 and its confidence interval at 5 % significance level, estimated according to two independently bootstrap estimate of both β_w and β_f. This allows us to appreciate the sensitivity of the simulated win-win development possibility with respect to the sampling variations. Specifically, for the net output gain, we say it is significantly greater than zero (which would indicate the win-win development) if the confidence interval does not include zero and values below zero. As reported in Table 2, except six sectors denoted above that do not approach the turning point in the forecasting period and six sectors with confidence interval including negative values and zero,[6] the remaining twenty six industrial sectors, 68.4 % of all sectors, enjoy a significant potential net output gain, a certain win-win development prospect without sample noise, in the last forecastingyear

[6] They are wood processing, general machinery manufacturing, special machinery manufacturing, transport equipment manufacturing, manufacturing of measuring instruments and machinery, and others.

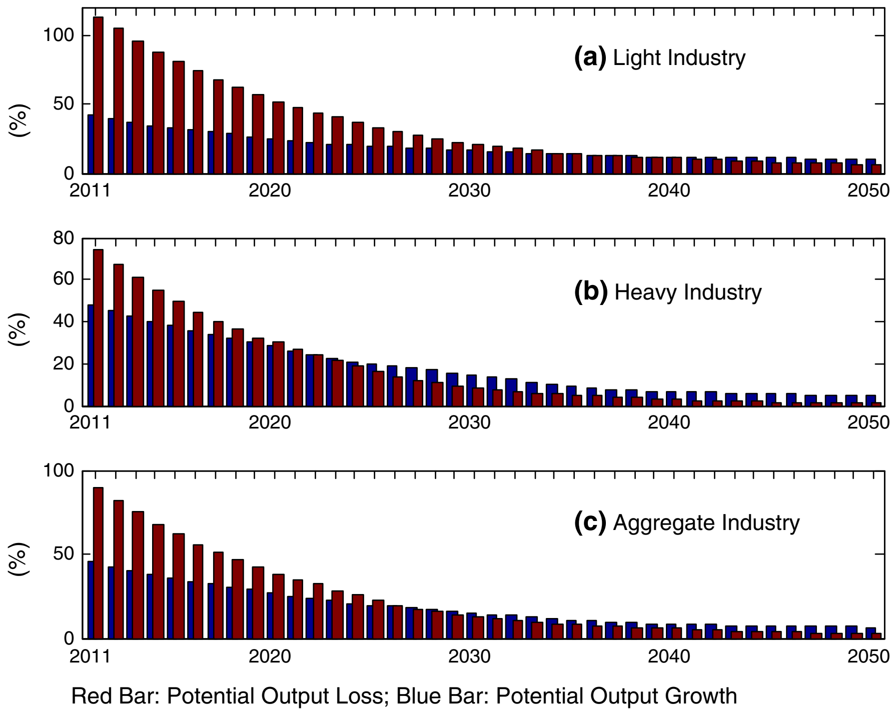

Fig. 3 Averaged win-win development forecasting under the best energy-saving and emission-abating path for light, heavy industry and the industry as a whole (2011–2050)

of 2050. All in all, the sectoral simulation results shown in Table 2 manifests that, from the perspective of potential output, environment regulations can bring costs on output which means that Porter hypothesis will not be satisfied in the very nearer future, but when the time moves on, it will lead to the win-win development prospect for most industrial sectors, finally supporting the Porter hypothesis.

According to the theory in Chenery et al. (1986) and current empirical work in Chen et al. (2011), the standard perception of industrialization is a general shift in relative importance from light to heavy industry. Light industry is of great importance normally at the early stage of industrialization and labor-intensive in nature with relatively low ratios of capital to labor; while heavy industry is at the middle or late stage and capital-intensive with relatively high ratios of capital to labor. Therefore, we divide all industrial sectors into light and heavy industrial groups according to the ranking of capital to labor ratio (K/L) in 2008. That is, the light industrial group corresponds to the top half of sectors with the lower K/L ratio, and the heavy industry to the last half of sectors with the larger K/L ratio. We refer to them as light industry and heavy industry in brief from now on in this paper. This is because 38 sectoral patterns of potential output growth and loss are too complicated to see clearly all at once, and sometimes we want to observe the difference just between the light and heavy industry instead. Figure 3 depicts the weighted average potential output loss (red bar) and output growth (blue bar) for light and heavy industry and aggregated industry, under the best environmental regulatory path, in which the sectoral weight is its respective share of gross industrial output value.

Seen from Fig. 3, in light industry, the averaged potential output loss declines prominently from −112.76 % in 2011 to −6.35 % in 2050 while the potential output growth decreases less evidently from 41.78 % in 2011 to 10.26 % in 2050; in heavy industry, the corresponding varying range is (−74.03 %, −0.97 %) for averaged potential output loss and (48.16 %, 4.88 %) for output growth. Basically, the potential output loss in light industry is higher than that in heavy industry over the entire forecasting time span while the output growth in light industry is lower than that in heavy industry before 2025 and exchanges the position since then. The light industry does not reach a comparable level for potential output loss and output growth until 2035 and keeps the similar situation to the beginning of 2040s, just right meeting the win-win development condition. But for the heavy industry, the win-win situation is reached even since the earlier year of 2023 and the potential output growth holds a relatively large advantage over the output loss since that year. Therefore, heavy industry is obviously the beneficiaries of energy save and emission reduction, but light industry is also not the losers. For the aggregated industry, the potential output loss declines from −89.69 % in 2011 to −2.62 % in 2050, the potential output growth decreases from 45.58 % in 2011 to 6.53 % at the end of the forecasting period-being between that of light and heavy industry. Since heavy industrial sectors have larger weights, the varying pattern of the potential output in aggregated industry looks more similar to that in heavy industry—realizing the win-win development in the year of 2027.

4.3 The influence of environment regulation on future industrial productivity

Sickles and Streitwieser (1998) have once investigated the impact of regulatory environment such as partial and gradual decontrol of natural gas prices on output change, technology and productivity in the interstate natural gas pipeline industry. Following this, this subsection also addresses the impact of optimal energy-saving and emission-abating activity on the foreseeable change of productivity, technique and efficiency in Chinese industry. Adopting the same group classification and weights as in Figs. 3, 4 exhibits the averaged changing trends of total factor productivity (TFP, i.e. MLPI) and its decompositions of MLTCH and MLECH under the optimal path of environment regulation for light, heavy and aggregated industry. Three subfigures show a similar pattern. That is, China's industrial TFP is firstly influenced by the efficiency change in which the catching-up effect of adoption of the frontier technologies due to the environment regulation is very obvious. When the efficiency attaches its utmost limits and the catching-up energy is almost released, the technical progress begins to serve as the major propelling force of industrial TFP through gradual accumulation and assimilation. The improvement of overall TFP index also reveals that the industrial development has generally shifted in a win-win fashion.

More specifically, at the early stage, energy-saving and emission-abating policy mainly negatively affects the industrial technical progress, and a little more on light industry than on heavy industry. For instance, for light industry, the level of techni-

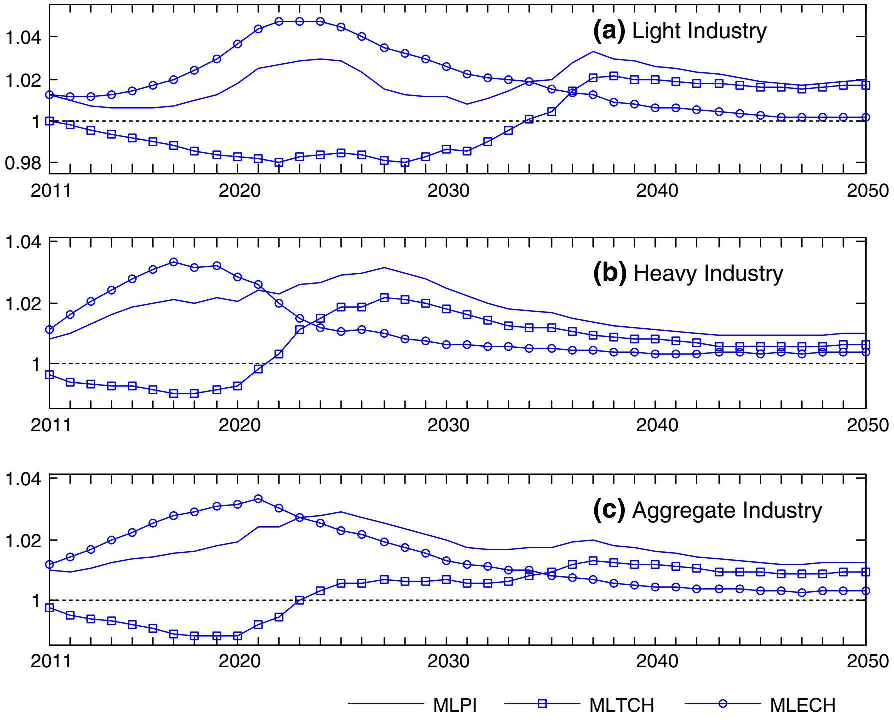

Fig. 4 Averaged productivity forecasting and its decomposition under the optimal energy-saving and emission-abating path (2011–2050)

cal progress in 2022 and 2028 is similarly 98.03 % of previous year, attaching the largest backward magnitude of production frontier, −1.97%, over the whole forecasting period; the largest backward extent of technical progress for heavy industry is −0.98 % in 2018 and the largest one for the aggregated industry is −1.16 % in 2019. However, due to the obvious catching-up effect and the improvement of production efficiency (at the efficiency peak, the value of MLECH is 1.048 in 2022 for light industry, 1.033 in 2017 for heavy industry, and 1.033 in 2021 for aggregated industry), the TFP growth will keep an increasing trend at the earlier forecasting phase. The negative effect of environmental regulation on technical progress fades gradually and turns to be positive in the year of 2034, 2022 and 2023 for light, heavy and aggregated industry, respectively; at the same time, the catching-up effect turns to decline and begins to be lower than the effect of technical progress in 2036, 2024 and 2035 for light, heavy and aggregated industry. The technical progress then gradually reaches its peak due to the long-term introduction, absorption, adoption and innovation of the advanced technologies—say, the technical progress attains the highest value of 1.021 in 2038, 1.021 in 2027, and 1.013 in 2037 for light, heavy and aggregated industry. After that, the efficiency continues to decrease while the industrial technique and its dominated productivity keep a steady growth till the end of forecasting period.

In a word, the optimal energy-saving and emission-abating activity plays a positive role in improving industrial productivity, though different role in technical progress and efficiency change in different period. For example, the TFP of light industry grows steadily to the first peak in 2024 (1.030) and attains the second peak in 2037 (1.033); while the TFP of heavy and aggregated industry increases first and turns to decline after reaching its peak in 2027 (1.032) and 2025 (1.029); in 2050 the TFP growth is 1.94, 0.97 and 1.27 % for light, heavy and aggregated industry, respectively. During the entire forecasting period from 2011 to 2050, on average the TFP growth of light, heavy and aggregated industry attains 1.80, 1.73 and 1.74 %, and the aggregated industrial technical progress and efficiency change reach to 0.34 and 1.42 %. This is a win-win development prospect since the productivity, technique and efficiency are growing and the targets to save energy and reduce emission are also achieved. As Chen and Golley (2014) denoted, the traditionally estimated TFP that does not take the energy and environment into account often overestimates the real TFP. In this paper, we also choose another model, named basic DEA approach to forecast the change of productivity, technique and efficiency in the same forecasting period, in which the CO2 emission will not be considered. The averaged change of productivity, technique and efficiency estimated by DEA approach over the entire forecasting time span is 2.34, 0.66 and 1.66 %, higher than their counterparts estimated by DAAM approach. To check the difference between basic DEA and DAAM measurements, we run the non-parametric Kolmogorov-Smirnov Z test in which the null hypothesis is that the DEA estimates are the same as the DAAM estimates. The test rejects the null hypothesis at the 0.000, 0.0108 and 0.005 significance level for series of productivity, technique and efficiency, respectively.

To investigate the heterogeneity and sensitivity of the estimates, we applied the bootstrap methods specified in Sect. 3.2 to test for significant differences from unity of sectoral Malmquist–Luenberger productivity index and its decomposition of technique and efficiency index, referring to Tables 3, 4 and 5, in which values greater than unity denote progress while values less than unity denote regress. Five adjacent time periods are exemplified. In 2011/2010, the original estimates tell us that the numbers of sectors that progress in productivity, technique and efficiency are 29, 24 and 33; while the bootstrapping test reveals that among them only 16, 5 and 15 sectors have a significant progress. Nine sectors regress in productivity in which only two of nonmetal products manufacturing and ferrous metals pressing are significant; 14 sectors decrease in technique and only 3 are significant (nonmetal ores mining, nonmetal products manufacturing, ferrous metals pressing); five sectors decrease in efficiency while only the sector of ferrous metals pressing is significant. In 2020/2019, twenty two sectors regress in technique and eighteen of them are significant, while sixteen sectors seem to progress in which there are only four to be significant, indicating a negative influence resulted from environment regulations. For change in efficiency, the original estimates tell us that thirty four sectors progress and the bootstrapping test denotes twenty seven of them are significant; four sectors that regress are all insignificant. Driven more by the efficiency, the performance of productivity looks not bad, in which twenty three sectors progress and only five are insignificant; fifteen sectors regress but only three are significant (textile manufacturing, leather manufacturing, and printing).

Table 3 Sectoral changes in productivity in selected years

Sectors	2011/2010	2020/2019	2030/2029	2040/2039	2050/2049
Coal	1.0051	0.9960	0.9971	1.0304*	1.0806**
Petroleum Ext.	1.0034*	1.0023*	0.9893	0.8551**	1.0000
Ferrous Mi.	0.9985	0.9930	1.0179*	0.9522*	0.9484**
Non-ferrous Mi.	1.0034	1.0093*	0.9982	0.9941	1.0053*
Nonmetal Mi.	0.9936	0.9866	0.9867	1.0002*	1.0017**
Wood Exp.	0.9920	0.9857	0.9865	0.9980	0.9990
Food Prod.	1.0031	1.0049	1.0031	1.0157**	1.0076*
Food Ma.	1.0021	1.0062	0.9989	1.0070*	0.9989
Beverage	1.0096	1.0097	1.0027	1.0038*	1.0024
Tobacco	1.0584**	1.0433**	1.0692***	1.0583**	1.0639***
Textile	1.0069*	0.9927*	0.9792*	0.9902	1.0076**
Apparel	1.0100*	0.9956	0.9886*	0.9887	0.9952
Leather	1.0037*	0.9933*	0.9923	1.0036*	1.0030
Wood Prod.	1.0012	0.9904	0.9859**	0.9907	0.9721
Furniture	1.0047	0.9953	0.9943*	0.9892	0.9723
Paper	1.0027	1.0063	0.9995	1.0086*	0.9909
Printing	1.0033	0.9935*	0.9907	1.0049**	1.0055*
Cultural articles	1.0069*	0.9971	0.9937*	1.0078**	1.0107**
Petroleum Prod.	0.9939	1.0049**	1.0038**	0.9973	1.0057*
Chemical products	1.0142**	1.0550***	1.0518***	1.0066*	1.0368**
Medicine	1.0025*	1.0059*	1.0030*	1.0066*	1.0075**
Fibers	1.2570***	1.0097**	1.0025*	1.0025*	1.0011*
Rubber	0.9999	0.9897	0.9866	1.0003*	1.0010
Plastic	1.0020	0.9916	0.9949*	1.0031*	0.9934
Nonmetal Ma.	0.9654**	1.0117**	0.9944	1.0355***	1.0348**
Ferrous press	0.8613***	1.0016*	1.1040**	1.0001	0.9799
Non-ferrous press	1.0030	1.0074*	1.0071*	0.9535*	0.9310*
Metal products	1.0037	0.9927	0.9909	1.0270**	1.0618***
General machinery	1.0081	1.0264**	1.0314**	1.0676**	1.0501**
Special machinery	1.0082*	1.0074*	1.0385**	1.0270**	1.0135*
Transport equipment	1.0358***	1.0308***	1.0314***	1.0202*	1.0133*
Electrical equipment	1.0508***	1.0532***	1.0098*	1.0092*	1.0029**
Computer	1.0095*	1.0157**	1.0142**	1.0017	1.0023**
Measuring instrument	1.0145**	1.0057*	1.0063*	1.0166**	1.0076*
Electric power	0.9983	0.9953	1.1336***	1.0079*	1.0866**
Gas Prod.	1.0030*	1.0056*	1.0026*	1.0038	1.0023*
Water Prod.	0.9994	1.0031	1.0609**	1.0775**	1.3265**
Others	1.0439**	1.0482**	1.0216**	1.0219**	1.0236*

Single, double and triple asterisks (*, **, ***) indicate significant differences from unity at 0.10, 0.05 and 0.01 level, respectively

Table 4 Sectoral changes in technique in selected years

Sectors	2011/2010	2020/2019	2030/2029	2040/2039	2050/2049
Coal	1.0049	1.0053	0.9958	1.0278*	1.0555**
Petroleum Ext.	1.0024	1.0044	0.9925	0.8612**	0.9656*
Ferrous Mi.	0.9978	0.9924	1.0005*	0.9791*	0.9482**
Non-ferrous Mi.	1.0023	1.0082	0.9993	0.9953	1.0003
Nonmetal Mi.	0.9934*	0.9864	0.9861	1.0003	1.0000
Wood Exp.	0.9918	0.9856*	0.9863	1.0002	1.0002*
Food Prod.	1.0027	1.0055	1.0006	1.0118**	1.0181**
Food Ma.	1.0016	1.0052*	0.9969*	1.0024*	0.9988
Beverage	1.0028	1.0054	1.0003	1.0007	0.9996
Tobacco	1.0029	1.0096	1.0776**	1.0526**	1.0544**
Textile	1.0059*	0.9917*	0.9844**	1.0004	1.0053*
Apparel	1.0072*	0.9928*	0.9858**	0.9882	0.9950
Leather	1.0001	0.9894**	0.9896*	1.0032*	1.0028*
Wood Prod.	1.0000	0.9893**	0.9856**	0.9880	0.9770
Furniture	0.9975	0.9883**	0.9864**	0.9835	0.9699*
Paper	1.0032	1.0055	1.0009	1.0094*	1.0134**
Printing	0.9983	0.9886*	0.9858*	1.0049*	1.0058*
Cultural articles	0.9986	0.9888*	0.9859**	1.0088**	1.0090*
Petroleum Prod.	0.9998	1.0035	0.9991	0.9606*	0.9531*
Chemical products	0.9994	1.0477**	1.0300**	1.0134**	1.0318**
Medicine	1.0012	1.0046**	1.0011	1.0037*	1.0048*
Fibers	1.0642**	1.0068	1.0000	0.9997	0.9997
Rubber	0.9991	0.9890*	0.9858	1.0004	1.0008
Plastic	1.0000	0.9897	0.9888	1.0041*	1.0058*
Nonmetal Ma.	0.9783**	0.9753**	0.9791**	1.0332**	1.0367**
Ferrous press	0.9147**	0.9583**	1.0623**	1.0010	0.9629*
Non-ferrous press	1.0029	1.0059	0.9846*	0.9675*	1.0226**
Metal products	1.0008	0.9898*	0.9879*	1.0321**	1.0605***
General machinery	0.9998	0.9852**	0.9877**	1.0396**	1.0400**
Special machinery	1.0071	0.9506***	0.9833**	1.0300**	1.0121**
Transport equipment	1.0013	0.9547**	1.0262**	1.0143**	1.0075*
Electrical equipment	1.0014	0.9960*	0.9875**	1.0053*	1.0022*
Computer	0.9995	1.0056	1.0096*	1.0007	0.9997
Measuring instrument	1.0129**	0.9492**	0.9865*	1.0111**	1.0065*
Electric power	1.0037	1.0015	1.0872***	1.0127**	1.0766***
Gas Prod.	1.0030*	1.0056**	1.0006*	0.9998	0.9996
Water Prod.	0.9988	0.9973	1.0497**	1.0744**	1.1519**
Others	1.0001	0.9693*	0.9902	1.0171*	1.0236*

Single, double and triple asterisks (*, **, ***) indicate significant differences from unity at 0.10, 0.05 and 0.01 level, respectively

Table 5 Sectoral changes in efficiency in selected years

Sectors	2011/2010	2020/2019	2030/2029	2040/2039	2050/2049
Coal	1.0002	0.9908	1.0013	1.0026**	1.0238**
Petroleum Ext.	1.0010	0.9980	0.9968	0.9929	1.0357**
Ferrous Mi.	1.0008	1.0006	1.0173	0.9725	1.0002
Non-ferrous Mi.	1.0011*	1.0011*	0.9989	0.9988	1.0050*
Nonmetal Mi.	1.0002	1.0002	1.0006	0.9999	1.0017
Wood Exp.	1.0002	1.0002*	1.0002	0.9978	0.9987
Food Prod.	1.0004	0.9995	1.0025*	1.0039	0.9897
Food Ma.	1.0004	1.0010*	1.0020*	1.0045*	1.0001
Beverage	1.0067*	1.0042*	1.0024*	1.0031*	1.0027
Tobacco	1.0554**	1.0334**	0.9922	1.0054*	1.0090
Textile	1.0010	1.0010	0.9947	0.9898	1.0023
Apparel	1.0028	1.0028*	1.0028*	1.0005	1.0002
Leather	1.0036**	1.0039**	1.0027**	1.0004	1.0002
Wood Prod.	1.0012	1.0012	1.0004	1.0027	0.9949
Furniture	1.0071**	1.0071**	1.0081**	1.0058*	1.0025
Paper	0.9995	1.0008*	0.9986	0.9992	0.9777
Printing	1.0050*	1.0050**	1.0050**	1.0000	0.9997
Cultural articles	1.0083**	1.0085**	1.0079**	0.9990	1.0017
Petroleum Prod.	0.9941	1.0013*	1.0047	1.0381**	1.0553**
Chemical products	1.0147**	1.0070*	1.0212**	0.9933	1.0048*
Medicine	1.0013	1.0013	1.0020	1.0029	1.0028
Fibers	1.1812**	1.0029*	1.0025	1.0028	1.0013
Rubber	1.0008*	1.0008*	1.0008	0.9999	1.0002
Plastic	1.0020*	1.0020*	1.0061	0.9990	0.9877
Nonmetal Ma.	0.9868	1.0373**	1.0157**	1.0022	0.9982
Ferrous press	0.9416**	1.0452***	1.0393**	0.9991	1.0177**
Non-ferrous press	1.0000	1.0015*	1.0229**	0.9855	0.9104**
Metal products	1.0029	1.0029	1.0031	0.9950	1.0012
General machinery	1.0083	1.0418**	1.0442**	1.0269**	1.0097
Special machinery	1.0011	1.0597***	1.0562***	0.9971	1.0015
Transport equipment	1.0344**	1.0797***	1.0051	1.0059*	1.0057
Electrical equipment	1.0493**	1.0574**	1.0226**	1.0039*	1.0007
Computer	1.0101*	1.0100*	1.0045	1.0010	1.0026
Measuring instrument	1.0016	1.0595**	1.0201**	1.0055	1.0011
Electric power	0.9947	0.9938	1.0427*	0.9953	1.0093*
Gas Prod.	1.0000	1.0000	1.0020	1.0041	1.0026
Water Prod.	1.0006	1.0058**	1.0106	1.0030*	1.1516*
Others	1.0438**	1.0814*	1.0318	1.0047	1.0000

Single, double and triple asterisks (*, **, ***) indicate significant differences from unity at 0.10, 0.05 and 0.01 level, respectively

In 2030/2029, twenty four sectors regress in technique and half of them are significant in which ten sectors belong to light industry except for nonmetal products manufacturing and non-ferrous metals pressing; fourteen sectors progress in technique and nine of them are significant (six sectors belong to heavy industry such as ferrous ores mining, chemical products manufacturing, ferrous metals pressing, electric power producing, gas producing, and water producing). Efficiency performs not bad; say, thirty three sectors increase in efficiency and seventeen of them are significant; while five sectors that regress are all insignificant. Thus, twenty sectors progress in productivity in which only two of them are insignificant, and eighteen sectors decrease in productivity with six being significant—such as textile manufacturing, apparel manufacturing, wood processing, furniture manufacturing, cultural articles manufacturing and plastic manufacturing, most of them belonging to light industry. In 2040/2039, twenty eight sectors progress in productivity, twenty six of which being significant; ten sector decrease in productivity with only three heavy industrial sectors being significant (i.e., petroleum extraction, ferrous ores mining, non-ferrous metals). For technique change, twenty eight sectors also progress in which only seven sectors are insignificant, ten sectors regress with only four sectors being significant. There are only ten sectors that have significant change in efficiency, and all the sectors that regress in efficiency are not significant. In 2050/2049, the sectors with significant efficiency change are very rare. Specifically, only nine sectors are significant in the change of efficiency, one of which regresses. There are twenty seven sectors that progress in technique and only three of which are insignificant; eleven sectors decrease in technique with only five sectors are significant. As for productivity change, twenty eight progress with only four sectors being insignificant; ten sectors regress in which only two of ferrous ores mining and non-ferrous metals pressing are significant. Obviously, the bootstrapping estimates reveal more accurate forecasting of sectoral change of productivity, technique and efficiency in the following 40 years than original point prediction.

5 Conclusion

To challenge the climate change and boost the transformation of development model, developing the low carbon economy under the appropriate environment regulations have become the necessary approach for most countries to achieve the sustainable economic development (Chen 2011). However, both energy save and environment protection will seize the important materials originally planned to normal production, causing the declination of the desirable output and competitiveness. The conflicting views are also reflected in academic area, i.e., if in favor or against the Porter hypothesis. This paper makes use of the directional distance function that precisely embodies the spirit of Porter hypothesis in which the goods increase and bads decrease simultaneously and proposes a novel dynamic activity analysis model (DAAM) to forecast the win-win development possibilities for Chinese industrial sectors between 2011 and 2050, to investigate the existence of Porter hypothesis in China. To overcome the sample variation, the consistent bootstrapping estimates are developed for forecasting both potential output and change of productivity, technique and efficiency in the following decades.

From the perspective of potential output, the empirical results show that, on average, energy save and emission reduction will cause relatively large potential output loss in an early stage; but in long run, the loss will decline gradually and become lower than potential output growth finally, achieving the win-win development prospect stated in Porter hypothesis. Specifically, the bootstrapping estimates reveal that twenty six industrial sectors, 68.4 % of all sectors, enjoy a statistically significant potential net output gain, a certain win-win development prospect without sample noise, in the last forecasting year of 2050. From the viewpoint of productivity, the prediction analysis manifests that energy-saving and emission-reducing policy will have a larger negative impact on industrial technical progress at an early stage, especially for light industry; however, due to the obvious catching-up effect and increasing production efficiency in the early forecasting period and the rising technical progress dominated in the latter period, the industrial TFP is not negatively influenced by the environment regulation and always maintains an increasing trend. During the entire forecasting period from 2011 to 2050, on average the TFP growth of light, heavy and aggregated industry attains 1.80, 1.73 and 1.74 %, respectively. The bootstrapping estimates also support that most sectors experience a progress in productivity, technique and efficiency. Overall, although energy-saving and emission-abating regulation will cause certain loss at an early stage, in the long run, it will not only reach the target of improving environment quality but also increase the output and productivity, finally leading to the win-win development in the following 40 years. Our forecasting analysis in this paper favors the Porter hypothesis.

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