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Toward green IT: Modeling sustainable production characteristics for Chinese electronic information industry, 1980–2012

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ABSTRACT

With the growth of the electronic information industry across the world, China has become a world factory of information technology products. However, the technology and energy efficiency of this industry in China are lower than those in other industrialized countries. In this study, the duality theory of non-radial directional distance function is used to develop a general procedure for modeling sustainable production characteristics for this industry. Using a non-radial efficiency model, environmental technical efficiency and environmental regulatory costs are estimated. In addition, the Porter hypothesis is tested using the Granger causality test. The shadow price of carbon emissions and inter-factor substitution possibilities can be measured using the dual model. The proposed methodology is employed to conduct an empirical study on Chinese electronic information technology manufacturing industry during 1980–2012. Finally, some policy implications are suggested.

1. Introduction

China's electronic information industry has enjoyed high-speed growth for almost three decades after its liberalization under national strategic policies, and now, this industry has become a pillar of the nation's economy. In 2013, the sales of China's electronics and information industry reached 12.4 trillion China Yuan (CNY), with a growth rate of 12.7%. The revenue accounts for 21.8% of the GDP, and more than 50% of the global IT revenue worldwide. In terms of manufacture of hardware, a total of 1.46 billion cell phones, 340 million computers, and 130 million TV sets were produced in China, accounting for more than 50% of the world's total production (http://www.china-industry-research.com/News/2013-saw-an-overall-smooth-operation-of-chinese-electronic-and-it-industry.html).

The electronic information industry produces a large amount of carbon emissions, discharging more than 830 million tons of carbon dioxide (CO_2) every year, which is approximately 2.0% of the global CO_2 emissions, the same as that produced by the aviation industry (http://www.natureworldnews.com/articles/467/20130107/ict-sector-account-2-percent-global-carbon.htm). Therefore, reducing the carbon emissions of the Information and communication technology (ICT) industry is critical to mitigating climate change word widely.

The gross production of the Chinese electronic information technology manufacturing (EIM) industry, and its CO_2 emissions, are shown in Fig. 1. Although the Chinese EIM industry has achieved high growth in terms of production, its CO_2 emissions have increased rapidly as well. Some developed countries such as the United States and Japan have achieved a negative growth in CO_2 emissions in the EIM industry, accomplishing the decoupling of CO_2 emissions and production. Thus, studying the sustainable production characteristics is key to the sustainable development of the Chinese EIM industry.

The remainder of this paper is organized as follows. Section 2 presents the literature review related to environmental production characteristics. Section 3 introduces the methodology of the non-radial directional distance function

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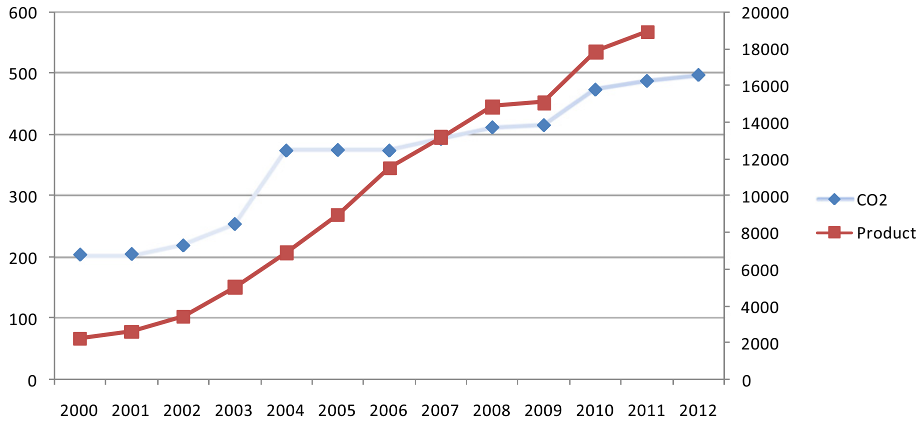

Fig. 1. CO_2 emissions and production in the EIM industry, China. Notes: CO_2 (10^4 T), Product (10^8 Yuan).
Source: Authors' calculations.

(DDF) approach, including measuring environmental technical efficiency, environmental regulatory cost, the shadow prices of emissions, and the Morishima elasticity of substitution among the factors therein. In Section 4, an empirical study of the Chinese EIM industry during 1980–2012 is conducted using the proposed methodology. Section 5 concludes and suggests some policy implications.

2. Literature review

Recognizing the importance of evaluating sustainable production, a number of studies have attempted to address the environmental and carbon efficiency issues in China. For instance, there have been studies conducted at a provincial-level (Hu and Wang, 2006; Choi et al., 2012; Zhang and Choi, 2013a), for industrial sectors (Shi et al., 2010; Wang et al., 2012; Wu et al., 2012), the iron and steel industry (Wei et al., 2007; Smyth et al., 2011; He et al., 2013), the manufacturing industry (Lee and Zhang, 2012), the power generation industry (Xie et al., 2012; Zhang and Choi, 2013b,c), and the transportation industry (Chang et al., 2013; Zhou et al., 2013). Although sustainable production efficiency in many sectors has been widely analyzed, no studies have focused on the EIM industry for China. Therefore, this study aims to fill this gap by investigating the sustainable production characteristics for EIM industry in China.

Among the various sustainable production modeling methods, the distance function approach has gained much popularity, possibly because it can model joint-production technology with good and environmental bad outputs simultaneously. Another possible reason is that unlike the cost function, the distance function does not require price-specific data that is relatively difficult to obtain. Given only the quantity data of inputs and outputs, which are easier to obtain, various critical environmental production characteristics can be formally studied, such as environmental technical efficiency, environmental productivity growth, the shadow prices of pollutants, and inter-factor substitution possibilities (Zhang and Choi, 2014).

Regarding using distance function for environmental studies, there are generally two kinds of distance functions that are widely used in the literature: The Shephard distance function (Shephard, 1970) and the directional distance function (DDF) (Chambers et al., 1996). The Shephard distance function expands the good and bad outputs proportionally, as much as possible. Thus, this method does not credit reduction of bad outputs, since all outputs are expanded at the same rate. On the other hand, the DDF, a relatively new approach for environmental production modeling, has attracted much attention recently. A major advantage of the DDF is that it is capable of expanding desirable outputs and contracting bad outputs simultaneously. Therefore, the DDF is a generalized form of the Shephard distance function and is more powerful and flexible.

Regarding to the specification, the DDF can be specified in at least two different ways: the parametric and the non-parametric approach. The parametric approach is based on a specific functional form that requires the adoption of a functional form, such as a translog or a quadratic function, for the distance function. It has the advantage of providing an estimated parametric representation of the sustainable production technology, which is differentiable and easy to manipulate algebraically. Therefore, the parametric method can be used to estimate the shadow prices of emissions (Färe et al., 1993) and the curvature or substitutability along the frontier (Lee and Zhang, 2012). On the other hand, the non-parametric approach, also called data envelopment analysis (DEA), is based on the construction of a piecewise linear combination of all observed outputs and inputs, and relies on mathematical programming. A major advantage of the DEA approach is that it does not require the imposition of a specific functional form on the underlying environmental technology. Therefore, non-parametric DDF provides an easier and more flexible means of estimation.

As the basic DDF (Chambers et al., 1996) aims to reduce inputs and expand outputs at the same rate, it can be regarded as a radial efficiency measure. However, the radial measure has several limitations, one of which is that a radial measure may lead to overestimate efficiency when the slacks exist (Fukuyama and Weber, 2009) and it has relatively weak discriminating power in ranking the entities to be evaluated (Zhou et al., 2007). To this end, recent studies sought to develop alternative non-radial DDF models (Zhang and Choi, 2013b,c; Fukuyama and Weber, 2009; Zhou et al., 2007; Färe and Grosskopf, 2010; Zhou et al., 2012; Zhang et al., 2013). Zhang and Choi (2014) presented an integrated literature review for modeling environmental production using DDF. Färe et al. (2005) first proposed a methodology based on the parametric DDF approach for modeling environmental production characteristics, including environmental technical efficiency, shadow pricing, and the elasticity of substitution for outputs. Lee and Zhang (2012) took advantage of parametric input distance function to model carbon production characteristics by estimating carbon technical efficiency, shadow prices of carbon emission, and elasticity of substitution for energy. However, the use of the non-parametric DDF approach to model environmental production characteristics has not yet been formally proposed.

This study contributes to the current body of literature by using the duality theory of DDFs to develop a general procedure for modeling sustainable production characteristics. Based on the non-radial DDF, environmental technical efficiency and environmental regulatory cost can be calculated, and then the Porter hypothesis is tested. By using the dual model of the DDF, both the shadow prices of emissions and the inter-factor Morishima elasticity of substitution can be derived. Calculations of energy substitution possibilities could give rise to some important suggestions for sustainable development. For the EIM industry, subject to environmental regulations, the high substitutability of capital for fossil fuel energy can help achieve the goal of "Green IT." Next section introduces the proposed methodology of non-radial DDF.

3. Methodology

In this section, the non-radial DDF model is presented, which contains the envelope model, which can evaluate environmental technical efficiency and regulatory cost, and the dual model, which can be used to estimate the shadow prices of undesirable outputs. Furthermore, based on shadow price ratios, Morishima elasticities of substitution for various factors can be derived.

3.1. Environmental technical efficiency

In order to introduce the non-radial DDF, firstly we need to explain the term "environmental production technology." Assume that there are $j = 1,\ldots, N$ decision-making units (DMUs). These can manufacture firms or industries. Suppose that each DMU uses input vector $x \in \mathfrak{R}_+^M$ to jointly produce good output vector $y \in \mathfrak{R}_+^S$ and bad output vector $b \in \mathfrak{R}_+^J$. The environmental production technology is expressed as:

$$T = \{(x, y, b) : x \text{ can produce } (y, b)\}, \tag{1}$$

where T is often assumed to satisfy the standard axioms of production theory, such as inactivity is always possible, and finite amounts of input can produce only finite amounts of output. In addition, inputs and desirable outputs are often assumed to be strongly or freely disposable. For the regulated environmental technologies, a weak disposability needs to be imposed on T. The weak-disposability assumption implies that reducing bad outputs, such as CO_2 emissions, are costly in terms of proportional reductions in production. The DEA piecewise linear production frontier is used to construct the environmental production technology. Then, regulated environmental technology T_1 for N DMUs exhibiting constant returns to scale can be expressed as

$$\begin{aligned} T_1 = \{(x, y, b) \quad : & \sum_{n=1}^{N} z_n x_{mn} \le x_m, m = 1, \ldots, M, \\ & \sum_{n=1}^{N} z_n y_{sn} \ge y_s, s = 1, \ldots, S, \\ & \sum_{n=1}^{N} z_n b_{jn} = b_j, j = 1, \ldots, J, \\ & z_n \ge 0, n = 1, \cdots, N\}. \end{aligned} \tag{2}$$

A formal definition of the non-radial DDF is proposed in Zhou et al. (2012) with undesirable outputs. Following Zhou et al. (2012), the non-radial DDF is defined as:

$$\vec{D}(x, y, b; g) = \sup\left\{\mathbf{w}^T \boldsymbol{\beta} : ((x, y, b) + g \cdot diag(\boldsymbol{\beta})) \in T\right\}. \tag{3}$$

where $\mathbf{w} = (w_m^x, w_s^y, w_j^b)^T$ denotes a normalized weight vector relevant to numbers of inputs and outputs, $g = (-g_x, g_y, -g_b)$ is an explicit directional vector, and $\beta = (\beta_m^x, \beta_s^y, \beta_j^b)^T \ge 0$ denotes the vector of scaling factors. The value of $\vec{D}(x, y, b; g)$ under the environmentally regulated technology can be calculated by solving the following DEA-type model:

$$\begin{aligned} \vec{D}^r(x, y, b; g) = \ & \max w_m^x \beta_m^x + w_s^y \beta_s^y + w_j^b \beta_j^b \\ \text{s.t.} & \sum_{n=1}^{N} z_n x_{mn} \le x_m - \beta_m^x g_{xm}, m = 1, \ldots, M, \\ & \sum_{n=1}^{N} z_n y_{sn} \ge y_s + \beta_s^y g_{ys}, s = 1, \ldots S, \\ & \sum_{n=1}^{N} z_n b_{jn} = b_j - \beta_j^b g_{bj}, j = 1, \ldots J, \\ & z_n \ge 0, n = 1, 2, \cdots, N \\ & \beta_m^x, \ \beta_s^y, \beta_j^b \ \ge 0. \end{aligned} \tag{4}$$

The directional vector g can be set up in different ways, based on given policy goals. If $\vec{D}\ (x, y, b; g) = 0$, then the specific unit to be evaluated is located on the frontier of best practices in the direction of g.

The environmental technical efficiency can be defined based on the non-radial DDF. As there are three inputs, one desirable output, and one undesirable output, we set the weight vector as $(1/3\,M, 1/3S, 1/3\,J)$ and the directional vectors as $g = (-x, y, -b)$, based on Zhou et al. (2012).

The overall environmental technical efficiency (ETE) for an industry is defined as the average efficiency of each factor. Suppose that β_x^*, β_y^*, and β_b^* represent the optimal solutions to Eq. (4), then the ETE can be formulated as:

$$\text{ETE} = 1 - \frac{1}{M+S+J}\left(\sum_{m=1}^{M} \beta_{xm}^* + \sum_{s=1}^{S} \beta_{ys}^* + \sum_{j=1}^{J} \beta_{bj}^*\right). \tag{5}$$

3.2. Environmental regulatory cost

To calculate the cost of environmental regulation, at first, the unregulated environmental technology should be introduced. Following Färe et al. (2007), the environmental regulatory cost measured by the opportunity cost of pollution abatement activities, estimated by the DDF, is the difference in production of good outputs associated with the unregulated and regulated environmental technologies.

The regulated environmental technology should meet the weak disposability assumption, as shown in Eq. (2), suggesting that reduction of the undesirable output is costly. If the industry does not face environmental regulations, which means that abatement of emissions is free and not costly, a strong disposability condition should be imposed on undesirable outputs, and thus, the following unregulated environmental technology (T_2) should be used.

$$T_2 = \{(x,y,b) \quad : \sum_{n=1}^{N} z_n x_{mn} \leq x_m, m = 1,\ldots,M, \\ \sum_{n=1}^{N} z_n y_{sn} \geq y_s, s = 1,\ldots,S, \\ \sum_{n=1}^{N} z_n b_{jn} \geq b_j, j = 1,\ldots,J, \\ z_n \geq 0, n = 1,\cdots,N\}. \tag{6}$$

Therefore, based on Färe et al. (2007), the value of $\overrightarrow{D}(x,y,b;g)$, under unregulated environmental technology, can be calculated by solving the following DEA-type model:

$$\overrightarrow{D}^u(x,y,b;g) = \max\ w_m^x \beta_m^x + w_s^y \beta_s^y + w_j^b \beta_j^b \\ \text{s.t.} \sum_{n=1}^{N} z_n x_{mn} \leq x_m - \beta_m^x g_{xm}, m = 1,\ldots,M, \\ \sum_{n=1}^{N} z_n y_{sn} \geq y_s + \beta_s^y g_{ys}, s = 1,\ldots S, \\ \sum_{n=1}^{N} z_n b_{jn} \geq b_j - \beta_j^b g_{bj}, j = 1,\ldots J, \\ z_n \geq 0, n = 1,2,\cdots,N \\ \beta_m^x,\ \beta_s^y, \beta_j^b\ \geq 0. \tag{7}$$

The environmental regulatory cost (ERC) is defined as good output loss associated with the unregulated and regulated environmental technologies. Technically, it can be expressed as follows:

$$ERC = \left[\beta_{yn}^u - \beta_{yn}^r\right] * y_n, \tag{8}$$

where β_{yn}^u is the optimal solution for DDF under unregulated technology in Eq. (7), while β_{yn}^r refers to the optimal solution to regulated technology, under DDF, in Eq. (4).

3.3. Shadow pricing and substitutability

In this subsection, the dual DDF model is used to estimate the shadow prices of environmental pollutants and the elasticities of substitution for inputs. The shadow cost function of a non-radial DDF is explained below.

The dual form of model (4) is as follows:

$$\min\ vx_0 - uy_0 + rb_0 \\ s.t. \\ vx - uy + rb \geq 0\ \forall n \\ v \geq \left[\frac{1}{g_1^x},\ldots,\frac{1}{g_m^x},\ldots,\frac{1}{g_M^x}\right] \\ u \geq \left[\frac{1}{g_1^y},\ldots,\frac{1}{g_s^y},\ldots,\frac{1}{g_S^y}\right] \\ r \geq \left[\frac{1}{g_1^b},\ldots,\frac{1}{g_j^b},\ldots,\frac{1}{g_J^b}\right]. \tag{9}$$

In Eq. (9), $\nu \in R^m$, $\mu \in R^s$, and $r \in R^j$ are the dual-variable vectors of the inputs ($x \in R^m$), good outputs ($y \in R^s$), and bad outputs ($b \in R^j$), respectively. The dual variables of the inputs, good outputs, and bad outputs can be estimated by the linear programming in Eq. (9). The dual model (9) aims to minimize the virtual cost of the industry concerned. Apparently, the dual DDF model is a type of cost maximization model, in which the virtual cost is at best zero (non-positive) when $\overrightarrow{D}^u(x,y,b;g) = 0$ for the DDF-efficient unit.

The dual variables $v \in R^m$ and $r \in R^j$ can be interpreted as the shadow prices of the inputs and undesirable outputs, respectively. $u \in R^s$ denotes the marginal virtual income of the good outputs. Assuming that the absolute shadow price of the undesirable outputs is equal to its market price (p^b), the relative shadow price of the undesirable outputs with regard to the good outputs (p^y) can be measured by:

$$r = u * \frac{p^b}{p^y}. \tag{10}$$

In other words, the shadow prices of the undesirable outputs can be interpreted as marginal abatement costs that represent the marginal rate of transformation between the undesirable and desirable outputs. Under the environmental regulations, abatement of pollutants is not free but costly for firms as they incur an opportunity cost associated with reducing a desirable output.

The curvature of the iso-quant curve reflects the degree of substitutability of the input factors in the production function. Following Lee and Zhang (2012), the elasticities of substitution between inputs x_i and x_j can be estimated by employing the idea of indirect Morishima elasticity of substitution, as shown in Eq. (11). The Morishima elasticity is defined as the shadow price ratio between the two factors, elucidated in Lee and Jin (2012). The Morishima elasticity for inputs captures the degree to which the relative shadow prices of inputs should be altered to allow substitutability among inputs along the iso-quant curve. A high value of the Morishima elasticity indicates low-level substitutability. It should be noted that $M_{ij} \neq M_{ji}$, because the ratios related to the two input shadow prices differ from each other, depending on which input is used as the basis. The degree of substitution of x_j for x_i does not coincide with the substitution of x_i for x_j in general. Since the non-radial DDF used in this study has a free-form orientation, we can also compute the elasticities of substitution between the undesirable outputs

b_r and b_s, as shown in Eq. (12).

$$M_{ij} = \frac{v_i}{v_j}, \tag{11}$$

$$M_{rs} = \frac{r_r}{r_s}. \tag{12}$$

4. Empirical analysis

In this section, the process of data collection of the inputs and outputs of the non-radial DDF framework is introduced. Annual industry data for the Chinese EIM industry from 1980–2012 is collected, after which the model evaluates the environmental technical efficiency, environmental regulatory cost, the shadow prices of pollutants, and the substitutability of factors.

4.1. Data collection

The models described in Section 3 will be applied to study the sustainable production characteristics of the Chinese EIM industry, from 1980–2012. First, data is collected pertaining to the inputs and outputs described in the framework.

For the output variables, the gross product (G) is selected to represent the sole desirable output, as in many previous studies (e.g., Lee and Zhang, 2012; Chen and Golley, 2014). Labor (L) and capital (K) are the two basic inputs of the production process. Employed labor force numbers are used as labor data. The data on gross product (G) and employees (L) of the EIM industry has been taken from the *China Statistical Yearbooks*.

Capital stock data are not available; however, they are calculated by the perpetual inventory method. Following this method, capital stock can be calculated as:

$$K_t = I_t + (1-\delta)K_{t-1}. \tag{13}$$

K_t, I_t, and δ represent the capital stock, investment in fixed assets, and depreciation rate at time t, respectively. K_{t-1} means the capital stock in period $t-1$. The depreciation rate for this industry, as shown in Chen and Golley (2014), is adopted, and the data related to investment in fixed assets is obtained from the *China Statistical Yearbook*. All the monetary variables, including gross product and capital stock, have been converted into 1990 prices with GDP deflators.

Recently, resources such as fossil fuels have also been selected as input variables (Hu and Wang, 2006; Choi et al., 2012; Zhang and Choi, 2013a). Therefore, total fossil fuel energy consumption, in standard coal equivalents, is selected as the energy input, including all types of energy (e.g., coal, oil, and gas). The energy data is from the *China Energy Statistical Yearbooks*.

CO_2 emissions are calculated based on the IPCC (International Panel on Climate Change) carbon emission factors by fossil-fuel types, as in Eq. (14):

$$CO_2 = \sum_i fc^i \times cv^i \times cc^i \times cor^i \times (44/12), \tag{14}$$

where i indicates the types of carbonaceous fossil fuels, fc^i is the amount of consumption of fuel i, cv^i is the average caloric value of fuel i, cc^i is the carbon content per unit calorie of fuel i, and cor^i is the carbon oxidation ratio for fuel i. Those values, by type of carbonaceous fuel, can be found in Lee and Zhang (2012).

The inputs and outputs are obtained for the model. Table 1 presents the descriptive statistics. We can see that the variations in the variables for Maximum and Minimum values vary substantially, and thus indicate substantial development of this industry during 1980–2012.

Table 2 presents the correlation matrix of the outputs and inputs. It clearly shows that the correlation coefficients between the outputs and inputs are almost significantly positive. Thus, when the inputs are increased, the output values will also increase. Thus, it is quite feasible to conduct an efficiency analysis in this case.

4.2. Empirical results

The environmental technical efficiency (ETE) is calculated based on Eq. (5) for the Chinese EIM industry during 1980–2012. The ETE results in Table 3 demonstrate that the EIM industry is not performing in an environmentally sustainable manner in many periods, as it employs a large amount of energy and produces large carbon emissions during the IT production process. The ETE scores varied from 0.142 to 1, with an average value of 0.551, indicating that the EIM industry, on average, can accomplish approximately a 44.9% ETE improvement, if this industry was to always operate on the frontier of environmental production technology.

Regarding the ETE trend of the EIM industry from 1980 to 2012, Fig. 2 shows that the ETE value was decreasing during 1980–1991; however, from the early 1990s, the efficiencies have shown a continual increase. Thus, the ETE shows a U-shaped trend, which suggests that during the 1980s, the development of the EIM industry was done in an unsustainable way, but after 1991, this industry manufactured IT products in a more eco-friendly manner.

The ERC of CO_2 emissions is calculated in terms of the opportunity cost of production given up to satisfy the environmental regulations. From Table 3, it is found that the average ERC is CNY 4.6 billion and the total ERC is CNY 151.8 billion, during 1980–2012. Fig. 3 shows the trend of ERC from 1980 to 2012, and it is observed that during the 1980s, there were no regulatory costs, indicating that carbon emissions were not regulated in the 1980s. From 1991 to 2005, the ERC began to increase rapidly. The increased ERC stems from the series of environmental regulation policies during the period. These included the policy of "grasping the large and letting go of the small," which lead to the closure of 84,000 small energy- and emission-intensive enterprises. In addition, the policy for developing renewable energy lead to the share of coal in energy

Table 1
Descriptive statistics of inputs and outputs, 1980–2012.

	Unit	Minimum	Maximum	Mean	Std. DV
G	10^8 Yuan	29.0	19883.3	4485.8	6494.8
K	10^8 Yuan	136.0	4224.6	1292.7	1241.0
L	Persons	116.0	1153.0	370.7	319.6
E	10^4 tons	113.0	2779.1	842.7	881.8
C	10^4 tons	205.0	537.0	367.7	98.4

Table 2
Correlation matrix of inputs and outputs.

	G	K	L	E	C
G	1				
K	0.886*	1			
L	0.896*	0.885*	1		
E	0.895*	0.893*	0.892*	1	
C	0.815*	0.235	0.337	0.871*	1

* Represents significance at the 5% level.

consumption falling from 75% in 1993, to 66 % in 2000, which lead to an increase in production costs (Chen and Golley, 2014). However, from 2006, the ERC suddenly fell to zero and stayed there until 2012. This surprising result indicates that during 2006–2012, although there were still some low-carbon policies implemented by the government, at the same time, the mechanization of heavy industry was overemphasized, while the monitoring and implementation of environmental policy were suspected. Our results are in accordance with Chen and Golley (2014).

Traditionally, economists think that environmental regulations necessarily bring additional cost to industry and thus, reduce the industry's productivity. However, some researchers have challenged this conventional view, arguing that strict environmental regulations can induce efficiency and encourage innovations that help improve industry competitiveness. This is the well-known Porter hypothesis (Porter and van der Linde, 1995). When testing the Porter hypothesis, it should be noted that it is important to identify the direction of causality between technical efficiency and environmental regulations. Stricter environmental regulations could lead to enhancement of technical efficiency, as suggested by the Porter hypothesis. However, innovation could also precede and lower the need for stricter regulations (Managi et al., 2005). Technical innovation in pollution control technology might lead to government environmental agencies to introduce stricter regulations that capitalize on the new technologies (Managi et al., 2005). In addition, economic development could drive an increased demand for environmental quality, as suggested in the environmental Kuznets curve. Therefore, there are two directions of causality between regulations and technical efficiency, and it is critical to identify which direction it is. The Granger causality test is used to investigate causal directions between the ERC and the ETE in this study. First, we estimate using the ETE as the dependent variable and ERC as the impendent variable, and vice-versa.

Table 3
ETE, ERC and SP for EIM industry, 1980–2012.

Year	ETE	ERC(10^8 Yuan)	SP (Yuan)
1980	0.567	0	474.6
1981	0.579	0	431.16
1982	0.431	0	460.702
1983	0.519	0	480.559
1984	0.415	0	497.69
1985	0.420	0	388.105
1986	0.423	0	164.587
1987	0.457	0	256
1988	0.397	0	156
1989	0.382	0	165.732
1990	0.188	0	59.198
1991	0.142	12.363	22.721
1992	0.149	17.205	36.428
1993	0.183	32.761	33.413
1994	0.224	45.232	20.877
1995	0.241	35.533	14.51
1996	0.233	30.634	12.713
1997	0.229	35.835	16.787
1998	0.322	70.529	16.628
1999	0.360	87.976	18.144
2000	0.475	113.964	17.103
2001	0.529	123.259	16.32
2002	0.629	148.352	14.78
2003	0.803	226.438	10.559
2004	1	245	9.591
2005	0.902	293.132	6.754
2006	1	0	0
2007	1	0	0
2008	1	0	0
2009	0.976	0	0.024
2010	1	0	0.03
2011	1	0	0.021
2012	1	0	0
Mean	0.551	46.006	115.204

As shown in Table 4, the Granger causality test indicates that the stringency of environmental regulations measured by the ERC Granger causes the ETE, thus supporting the Porter hypothesis. It is also found that there is a significant causal link between the ETE and the ERC, which indicates that higher ETE will also lead to higher ERC (stricter regulation).

As shown in Table 3, the estimated shadow prices for the CO_2 emissions, calculated via Eq. (11), can be interpreted as measures of the opportunity cost of emission abatement. Therefore, the shadow prices measure the marginal abatement cost of CO_2 emissions of the EIM industry in general. From Table 3, it is found that the EIM industry, on average, pays CNY 115.2 to abate 1 ton of CO_2 emissions during the research period. The marginal abatement costs of CO_2 emissions for 1980–2012 range from zero (2006–2008) to CNY 497.7 (1984). Table 5 compares the shadow price result with those of previous studies for China. The results of these previous studies lie in a wide range depending on the usage of different dataset for different industries and estimation method.

According to the 12th five-year plan of the Chinese government, carbon ETSs are planned in some pilot regions of Beijing, Chongqing, Shanghai, Tianjin, Hubei, and Guangdong from 2011 onwards. This pilot system shall be expanded in to a unified national system by 2015. If CO_2 emission standards are enforced by regulation and carbon emission trading markets are formulated in China, a comparison of carbon shadow price between the EIM and other industries could achieve substantial benefits from trading emission permits. The estimation result of the CO_2 shadow price of the EIM industry is higher than the market price of national CO_2 emissions trading. For instance, the national market price for carbon emission trading is quoted as CNY 51 in the Beijing market, as of 30 September 2014.[1] Thus, this industry might buy the trading emission permits from other industries to achieve cost savings.

The dynamic trend of shadow prices is shown in Fig. 4. It is found that the shadow price of CO_2 emissions shows a downward trend during 1980–2012. There are two possible reasons for this downward trend; first, the marginal abatement cost of an emission is negatively related to the amount of the pollutant. If the emission amount is large, the marginal

[1] http://www.tanpaifang.com/tanshichang/.

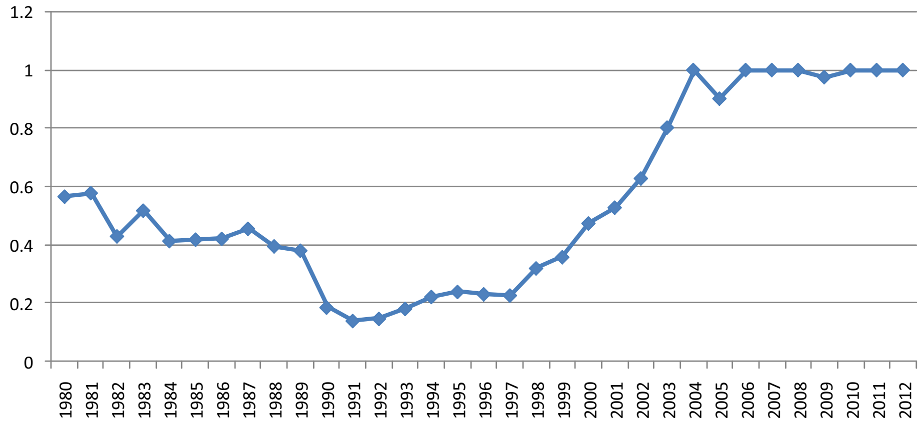

Fig. 2. Environmental technical efficiency of the EIM industry, 1980–2012.

abatement cost will be relatively low; while, if the emission amount is small, marginal abatement cost will be relatively high (Turner et al., 1993). As the amount of CO_2 emissions of the EIM industry increased over time, the related shadow price decreased. Another possible reason for decreased shadow price is due to policy factors, as discussed previously, though the monitoring and implementation mechanism of carbon reduction policy are not well developed in China.

Table 6 presents the indirect Morishima-type elasticities of substitution between individual inputs calculated from Eq. (12), which are evaluated based on the inputs' shadow price ratio. The lower value of M_{kl}, relative to M_{lk}, indicates that labor is more readily substituted for capital, which reflects the Chinese EIM industry's labor-intensive characteristics. A lower M_{el} value, relative to M_{le}, indicates that labor is more easily substituted with energy. This result also reflects the labor-intensive nature of this industry.

Regarding the degree of substitution of capital for energy, it is found that M_{ek} is greater than M_{ke}, indicating that the substitutability of capital for energy may be lower than that of energy for capital. Both M_{ek} and M_{ke} are lower than M_{lk} and M_{kl}, indicating that capital and energy are substitutes in the EIM industry in general. In investigating the trend of M_{ek} and M_{ke}, it is found that after 1995, both M_{ek} and M_{ke} are valued at zero, indicating that capital and energy have strong substitutability.

This finding indicates the high substitutability of capital for energy in this industry. If the EIM industry succeeds in investing in energy-efficient capital, this industry is likely to achieve the goal of "sustainable development." Additionally, through the appropriate use of funds gathered through energy and carbon-related taxes, with the government's policy assistance, this industry could invest in energy-efficient capital to achieve sustainability.

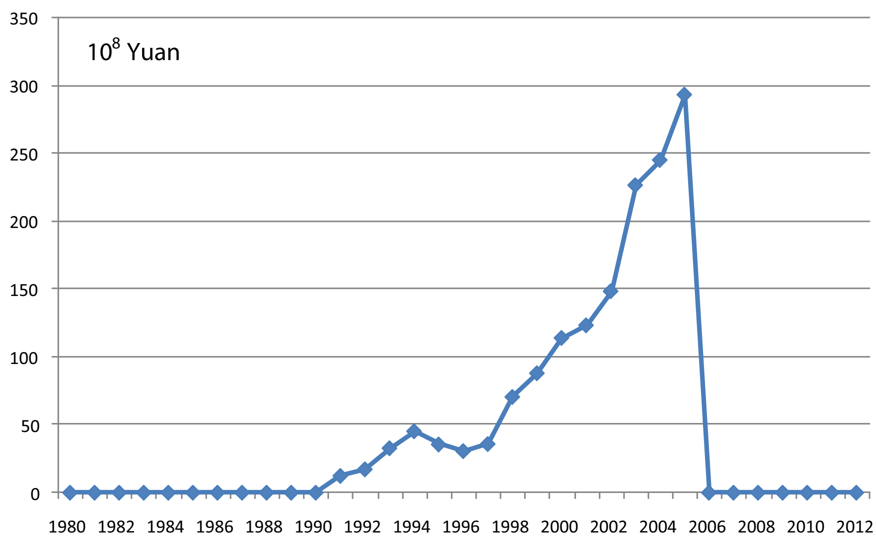

Fig. 3. Environmental regulatory cost of CO_2 emissions, 1980–2012.

Table 4
Granger causality test for ERC and ETE.

Null hypothesis	Obs	F-statistic	Prob.
ERC does not Granger cause ETE	31	3.58687	0.0421
ETE does not Granger cause ERC		10.2049	0.0005

5. Conclusion

As the EIM industry in China grows rapidly, it does not do so in a sustainable way, with high-energy use and large carbon emissions. This study examines the sustainable production characteristics for this industry during 1980–2012. It uses the duality theory of a non-radial DDF to develop a general methodology for modeling sustainable production characteristics, based on a non-parametric approach. Using the non-radial DDF, we measure environmental technical efficiency, environmental regulation cost, and the causality between them, to test the Porter hypothesis. By using the dual model of non-radial DDFs, the shadow prices of carbon emissions and inter-factor substitution possibilities are empirically investigated.

The empirical results are summarized as follows: First, the ETE shows a U-shaped trend, which indicates that the development of the EIM industry was not done in an eco-friendly way during the 1980s, and transferred to a more sustainable practice after the 1990s. Second, the ERC began to increase rapidly from 1991 to 2005 due to the series of environmental regulation polices, but suddenly fell to zero till the end of the study because of the overemphasis on industrialization of heavy industry and the absence of policy monitoring and implementation. Third, the Granger causality test indicates that the stringency of environmental regulations causes technical innovation, which supports the Porter hypothesis and finds that higher technical efficiency will also lead to stricter environmental regulation. Fourth, the shadow price of CO_2 emissions shows a downward trend during 1980–2012 because of continued increase in the amount of emissions and weak carbon emission regulation. Finally, the Morishima elasticity of substitution indicates the high substitutability of capital for energy. The related policy implications are proposed as follows: First, because the tougher environmental regulations could spur innovation, leading to increased productivity in EIM industry, the government is suggested to propose well-developed environmental regulations. Second, the monitoring and implementation mechanism of carbon reduction policy should be enhanced for Chinese EIM industry. Finally, via the appropriate use of funds gathered through energy and carbon related taxes imposed by the government, this industry could invest in energy-efficient capital that leads to achieving sustainable development.

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Table 5
Shadow prices comparison with previous studies.

Previous studies	Method	Period	Sample	Shadow price (Yuan/ton)
Choi et al. (2012)	DEA	2001–2010	30 provinces	41.2–46.9
Wang et al. (2011)	DEA	2007	30 provinces	475.3
Lee and Zhang (2012)	Parametric	2009	30 manufacturing industries	0–113.4
Wei et al. (2012)	DEA	1995–2007	30 provinces	114
Wei et al. (2013)	Parametric	2004	124 power plants	612.6–2059.8
Du et al. (2014)	Parametric	2001–2010	30 provinces	1000–2100
This study	DEA	1980–2012	EIM industry	0–497.7

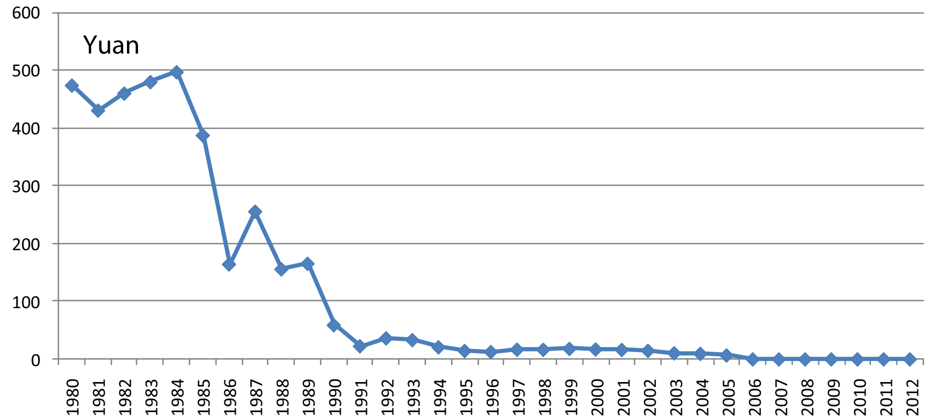

Fig. 4. Shadow price of CO_2 emissions, 1980–2012.

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Table 6
Morishima elasticity of substitution for inputs.

DMU	M_{kl}	M_{lk}	M_{el}	M_{le}	M_{ek}	M_{ke}
1980	0.400	2.502	0.000	0.000	0.000	0.000
1981	0.000	0.000	0.000	0.000	1.963	0.509
1982	0.000	0.000	0.000	0.000	1.963	0.509
1983	0.000	0.000	0.000	0.000	1.963	0.509
1984	0.000	0.000	0.851	1.176	0.000	0.000
1985	0.000	0.000	15.054	0.066	0.000	0.000
1986	0.000	0.000	0.000	0.000	0.000	0.000
1987	0.000	0.000	0.000	0.000	0.000	0.000
1988	0.355	2.816	0.764	1.309	2.152	0.465
1989	0.400	2.502	0.000	0.000	0.000	0.000
1990	0.000	0.000	0.851	1.176	0.000	0.000
1991	0.000	0.000	0.000	0.000	36.189	0.028
1992	0.646	1.548	0.681	1.468	1.054	0.949
1993	0.400	2.502	0.000	0.000	0.000	0.000
1994	1.616	0.619	2.583	0.387	1.598	0.626
1995	0.000	0.000	0.000	0.000	0.000	0.000
1996	0.000	0.000	0.000	0.000	0.000	0.000
1997	0.000	0.000	0.236	4.235	0.000	0.000
1998	0.000	0.000	0.236	4.235	0.000	0.000
1999	0.000	0.000	0.054	18.381	0.000	0.000
2000	0.000	0.000	0.054	18.380	0.000	0.000
2001	0.000	0.000	0.054	18.381	0.000	0.000
2002	0.000	0.000	0.054	18.381	0.000	0.000
2003	0.000	0.000	0.000	0.000	0.000	0.000
2004	0.000	0.000	0.000	0.000	0.000	0.000
2005	0.000	0.000	0.236	4.235	0.000	0.000
2006	0.000	0.000	0.000	0.000	0.000	0.000
2007	0.182	5.501	0.000	0.000	0.000	0.000
2008	0.511	1.955	0.000	0.000	0.000	0.000
2009	0.000	4862.111	0.000	0.000	0.000	0.000
2010	0.000	0.000	0.000	0.000	0.000	0.000
2011	0.000	5617.689	0.000	0.000	0.000	0.000
2012	0.000	0.000	0.000	0.000	0.000	0.000
Mean	0.137	318.174	0.658	2.782	1.421	0.109

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