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Interaction between output efficiency and environmental efficiency: evidence from the textile industry in Jiangsu Province, China

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A B S T R A C T

Environmental efficiency improvement has played a crucial role in the theory and practice of stimulating clean production. This paper analyzes the interaction between environmental efficiency and output efficiency, particularly whether they reinforce each other or compete with each other, on the basis of a data set of 137 firms in the textile industry in China's Jiangsu Province. In the first stage, generalized data envelopment analysis is applied to calculate efficiency measures of energy, waste water, waste gas, soot, and output efficiency taking capital, labor, water, and energy as inputs, industrial output value as desirable output, and waste water discharges, waste gas and soot emissions as undesirable outputs. In the second stage analysis, a structural equation model with latent variables is applied to analyze the interaction between the latent variable environmental efficiency, measured by the four observed environmental indicators, and output efficiency, taking also into account the endogenous variable profit. The main outcomes of the structural equation model are the following. Firstly, environmental efficiency negatively impacts on profit while profit positively impacts on environmental efficiency. In a similar vein, output efficiency is found to depress profit while profit increases output efficiency. Thirdly, environmental efficiency has a positive impact on output efficiency while there is no effect of output efficiency on environmental efficiency. Fourthly, taxes impair a firm's output efficiency. From the findings it follows that a swap of general taxes for an energy tax is likely to improve both output efficiency and energy efficiency. The latter outcome implies a win–win situation which will facilitate the further implementation and adoption of environmental policy. Finally, the paper illustrates the applicability of structural equation modeling in efficiency analysis.

1. Introduction

Environmental efficiency improvement has played a crucial role in the theory and practice of stimulating clean production. Nevertheless, the determinants and impacts of environmental efficiency are not fully understood yet. This applies in particular to the relationship between environmental efficiency and output efficiency. There are two possible effects of environmental efficiency, notably energy efficiency, on output efficiency. First, a positive effect in that an environmentally friendly/energy efficient firm has lower energy costs which, ceteris paribus, improves its output efficiency. On the other hand, improving environmental efficiency implies opportunity costs in that the resources used to improve environmental efficiency could have been used to improve output efficiency. Furthermore, not only may environmental efficiency impact on output efficiency, but also vice versa: output efficiency may impact on environmental efficiency. Again, there are two possible effects. First, a positive effect in that output efficient firms have more resources to improve environmental efficiency than output inefficient firms, ceteris paribus. Secondly, a negative effect in that improving output efficiency absorbs resources to improve environmental efficiency.

Environmental efficiency, notably energy efficiency, has played a crucial role in China. Its unprecedented economic growth has been accompanied by a dramatic increase in energy consumption. It has

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risen more than sixfold over the past 35 years, from 571 million tons standard coal equivalent (SCE) in 1978 to 3750 in 2013 (NBS, 2014). China is now the world's largest energy consumer (Liao et al., 2007; Wang et al., 2012; Bian et al., 2013). In 2013, it accounted for 22.4% of global primary energy consumption (BP, 2014). Specifically, it consumed approximately 12.12% of global oil, nearly 5% of global natural gas, about 50% of global coal, and 24% of global hydro power. Besides, it has become one of the largest energy producers in the world (Herrerias et al., 2013). For example, in 2013 China's coal production accounted for nearly half of the world's total (BP, 2014).

China's energy consumption has led to two major challenges, viz. energy shortage and environmental degradation (Song et al., 2011; Meng et al., 2013; Lin and Ouyang, 2014). Regarding the first challenge, China has been suffering from a rapidly widening energy gap for more than two decades. In 2013, there was a deficiency of 350 million tons SCE (NBS, 2014), accounting for 9.3% of China's energy consumption of 3750 million tons SCE. Consequently, China has expanded its energy imports, particularly of oil. In 2013, imports of oil accounted for nearly 70% of China's total oil consumption (NBS, 2014).

Regarding the second challenge, environmental degradation in China has been worsening due to emissions of various pollutants caused by fossil fuel combustion (Yong and Oberheitmann, 2008; Wang et al., 2012). In 2012, SO_2 emissions totaled 21.2 million tons, NO_x emissions 23.4 million tons, smoke and dust 12.4 million tons, and CO_2 emissions 9.9 billion tons (NBS, 2013; Netherlands Environmental Assessment Agency, 2013). SO_x and NO_x, which are the main causes of acid rain, have affected about 300 cities in China (Zhang et al., 2011). Economic losses caused by fossil fuel combustion based pollution accounted for 3.9% of China's GDP in 2008 (Li et al., 2013). Coal combustion is the main source. Specifically, 90% of SO_x, 67% of NO_x and 70% of total CO_2 emissions in China result from coal combustion (Fang and Zeng, 2007).

Energy efficiency improvement has played a crucial role in addressing both energy shortage and environmental degradation in China (Tanaka, 2008; Andrews-Speed, 2009). Its improvement has been regarded as a top priority by the Chinese central government for years. In the 11th Five-Year Plan (2006–2010), the Chinese government for the first time launched a nationwide campaign aimed at improving energy efficiency. To this end, the Plan specified targets for each provincial government. In a similar vein, municipal governments were assigned targets by their provincial governments.

Adequate measures of energy efficiency can be obtained by means of stochastic frontier analysis (SFA) and data envelopment analysis (DEA) (see Hu and Wang, 2006; Chien and Hu, 2007; Martínez, 2011). SFA is a parametric approach that requires functional specifications. Furthermore, it takes only one output into consideration. DEA, proposed by Charnes et al. (1978), on the other hand, is a non-parametric (optimization) approach that can deal with a system of multiple outputs and inputs (Wu et al., 2014). Moreover, it does not require functional specifications between the inputs and the outputs (Seiford and Thrall, 1990; Shi et al., 2010; Wu et al., 2014). Another advantage is that it only requires information on the physical quantities of inputs and outputs (Abbott, 2006). Consequently, it has gained great popularity in measuring energy efficiency (Zhou et al., 2014). For example, Wei et al. (2009) used DEA to measure energy efficiency of 29 Chinese Provinces for the period 1997–2006. The author found that the eastern region had the highest energy efficiency score, the western region the lowest while the central region had an in-between position. Another application is Martínez (2011) who applied DEA to measure energy efficiency development in non energy-intensive sectors in Germany and Colombia during the period 1998–2005. The author found that the average energy efficiency scores were similar in both countries. Thirdly, Blomberg et al. (2012) evaluated electricity efficiency of more than 30 pulp and paper mills for the year 1995, 2000 and 2005 by means of DEA. They observed that the electricity efficiency gap among the mills was relatively stable over time.

Conventional DEA models proceed on the basis of the assumption that inputs are minimized and economic output is maximized in the production process (Scheel, 2001; Jahanshahloo et al., 2005). This assumption ignores the fact that production not only produces desirable output, but also undesirable outputs, particularly emissions (Färe and Grosskopf, 2004; Färe et al., 2005; Zhou et al., 2007; Liu et al., 2010; Wang et al., 2012, 2013; Pérez-Calderón et al., 2011; Wu et al., 2014; Chen et al., 2015). If undesirable outputs, e.g. pollutants, are ignored in (energy) efficiency evaluation, a distorted picture of (energy) efficiency may result. Both desirable (goods) and undesirable outputs (bads) should be considered in efficiency analysis (Seiford and Zhu, 2002; Rashidi et al., 2015; Song et al., 2012). DEA that takes both goods and bads into account is denoted here as generalized DEA (GDEA).

The basic notion to incorporate both goods and bads (e.g. pollutants) in the DEA framework originates from Pittman (1983)'s seminal work. In recent years, it has gained popularity in energy efficiency analysis. For example, Sözen et al. (2010) in their generalized efficiency analysis of 15 thermal power plants in Turkey, took thermal efficiency, operational time, and fuel cost as inputs, electricity as desirable output, and CO_2, SO_2, N_2O, CH_4, CO, NO_x, and non-methane volatile organic compounds (NMVOC) emissions as undesirable outputs. They found that there was a large efficiency gap across the 15 thermal power plants. Another application is Sueyoshi and Goto (2014) who used three inputs, viz. assets, employees and energy, in their generalized efficiency analysis of 31 Japanese chemical and pharmaceutical firms. They took sales as desirable output, and greenhouse gas emissions and waste discharges as undesirable outputs. They found that the pharmaceutical firms outperformed the chemical firms.

There are also some Chinese studies that took undesirable outputs into account. For example, Shi et al. (2010) measured industrial energy efficiency of 28 provinces for the period 2000–2006, taking assets, labor, and energy as inputs, industrial added value as desirable output, and waste gas as undesirable output. They found that the eastern region had the highest average energy efficiency score, followed by the central and western regions. Wang et al. (2012) used capital stock, labor, coal, oil, and natural gas as inputs, gross provincial product as desirable output, and CO_2 and SO_2 as undesirable outputs to measure energy efficiency of China's 30 Provinces for the period 2000–2009. In line with Shi et al. (2010), the eastern provinces were found to have the highest energy efficiency scores, followed by the central and western provinces. Wang et al. (2013) and Li et al. (2013) reported energy efficiency scores for 29 Chinese Provinces during the period of 2000–2008 and 1991–2001. They took gross provincial product as desirable output, capital stock, labor and energy as inputs, CO_2 emissions and SO_2 emissions as two undesirable outputs, while the latter also considered waste water, waste gas and solid waste as undesirable outputs. Again, the eastern provinces were found to have the highest energy efficiency score, followed by the central provinces and the western provinces.

Few studies have been conducted at firm level in China. An exception is He et al. (2013), who evaluated energy efficiency of 50 large iron and steel enterprises taking three undesirable outputs, viz. waste gas, waste water and solid waste, into consideration. They found that the average energy efficiency was only 0.611. We have not been able to find empirical efficiency studies for small and medium-sized firms in China in the literature which is probably due to data limitations.

The existing literature has merely paid attention to the calculation of efficiency and ignored the possible interaction between desirable output efficiency and environmental efficiency. The present paper intends to fill this gap. It analyzes the interaction between environmental efficiency and output efficiency based on a data set of 137 small and medium-sized textile firms in China's Jiangsu Province in 2009. First, output efficiency and environmental efficiency indicators are estimated by means of GDEA taking capital, labor, water, and energy as inputs. Next, a structural equation model (SEM) with output efficiency and environmental efficiency as interacting latent endogenous variables will be estimated.

The structure of the paper is as follows. Section 2 briefly summarizes the GDEA and SEM. Section 3 describes the study area and data sources while Section 4 presents the empirical results. Section 5 concludes and presents policy recommendations.

2. Methods

Generalized data envelopment analysis (GDEA) is introduced in subsection 2.1. In Section 4, it will be applied to calculate the efficient levels of the inputs which in their turn are used to calculate indices of energy efficiency (*EEF*), waste water efficiency (*WWEF*), waste gas efficiency (*WGEF*), soot efficiency (*STEF*), and output efficiency (*OutEF*) for each firm. The output of GDEA (the four environmental measures) are input into the SEM which will be applied to analyze the interaction between output efficiency and environmental efficiency, measured by the above four environmental indices. The SEM is summarized in subsection 2.2.

2.1. Generalized DEA (GDEA)

Consider a production system with n decision making units (DMUs). The production has inputs, desirable (good) outputs and undesirable (bad) outputs, represented by three vectors: $x \in R^m$ (inputs), $y^g \in R^{q_1}$(desirable or good output), and $y^b \in R^{q_2}$ (undesirable or bad output), respectively. Furthermore, let m, q_1 and q_2 represent the number of inputs, desirable outputs and undesirable outputs, respectively. The input matrix X, the desirable output matrix Y^g, and the undesirable output matrix Y^b are defined as: $X = [x_1,\ldots,x_n] \in R^{m \times n}$, $Y^g = [y_1^g,\ldots,y_n^g] \in R^{q_1\times n}$, $Y^b = [y_1^b,\ldots,y_n^b] \in R^{q_2\times n}$. It is assumed that all inputs and outputs are non-negative.

The production possibility set (P) is defined as:

$$P = \left\{\left(x, y^g, y^b\right) \middle| \mathbf{x} \ge X\lambda, \mathbf{y}^g \le Y^g\lambda, \mathbf{y}^b \le Y^b\lambda, \lambda \ge 0\right\} \tag{1}$$

where λ is the intensity vector.

As an introduction to GDEA, the calculation of the efficiency of DMU at (x_0,y_0), denoted MNU (x_0,y_0) with only one (good) output is first considered.[1] The slack-based measure (SBM) approach first proposed by Tone (1997, 2001) is adopted, which is formulated as the following minimization program[2]:

$$\min\rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1 + \frac{1}{q}\sum_{r=1}^{q}\frac{s_r^+}{y_{r0}^g}} \tag{2}$$

$$\text{Subject to} \quad x_0 = X\lambda + s^- \tag{3}$$

$$y_0 = Y\lambda - s^+ \tag{4}$$

$$s^- \ge 0, s^+ \ge 0, \lambda \ge 0 \tag{5}$$

where vectors s^- and s^+ are the slack variables representing excesses input and output shortage, respectively. The value of ρ is the efficiency score at (x_0,y_0).

To take undesirable outputs into account, system (2)–(5) can be modified to evaluate DMU (x_0, y_0^g, y_0^b) as follows (Li and Shi, 2014):

$$\rho = \min\frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1 + \frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1}\frac{s_r^g}{y_{r0}^g} + \sum_{r=1}^{q_2}\frac{s_r^b}{y_{r0}^b}\right)} \tag{6}$$

$$\text{Subject to} \quad x_0 = X\lambda + \mathbf{s}^- \tag{7}$$

$$y_0^g = Y^g\lambda - \mathbf{s}^g \tag{8}$$

$$y_0^b = Y^b\lambda + \mathbf{s}^b \tag{9}$$

$$\mathbf{s}^- \ge 0, \mathbf{s}^g \ge 0, \mathbf{s}^b \ge 0, \lambda \ge 0 \tag{10}$$

where the vector s^b refers to excesses in undesirable outputs and the vector s^g denotes shortages in desirable outputs. ρ is called the DMU's generalized efficiency (*GEF*) score at DMU (x_0, y_0^g, y_0^b). It satisfies $0 \le \rho \le 1$.

System (6)–(10) is a nonlinear program that can be transformed into a linear program (LP) by means of the Charnes-Cooper transformation as follows (Charnes and Cooper, 1962; Li et al., 2013; Chang et al., 2013; Li and Shi, 2014). The transformation is as follows. First, following Charnes and Cooper (1962), a scalar variable t ($t > 0$) is included into system (6)–(10) that multiplies both the denominator and the numerator of (6), and thus does not change ρ. Furthermore, the denominator is made equal to 1 by adjusting t, and, next, it is specified as a constraint ((12) below). The objective then is minimization of the numerator. System (6)–(10) now reads (Tone, 2001):

$$\tau = \min t - \frac{1}{m}\sum_{i=1}^{m}\frac{ts_i^-}{x_{io}} \tag{11}$$

$$\text{Subject to} 1 = t + \frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1}\frac{ts_r^g}{y_{ro}^g} + \sum_{r=1}^{q_2}\frac{ts_r^b}{y_{ro}^b}\right) \tag{12}$$

$$x_0 = X\lambda + \mathbf{s}^- \tag{13}$$

$$y_0^g = Y^g\lambda - \mathbf{s}^g \tag{14}$$

$$y_0^b = Y^b\lambda + \mathbf{s}^b \tag{15}$$

$$\mathbf{s}^- \ge 0, \mathbf{s}^g \ge 0, \mathbf{s}^b \ge 0, \lambda \ge 0 \tag{16}$$

System (11)–(16) contains the nonlinear term *ts*. It can be transformed into a linear program by defining $S^- = ts^-$, $S^g = ts^g$, $S^b = ts^b$ and $\Lambda = t\lambda$. Accordingly, system (11)–(16) becomes the following linear program (Tone, 2001):

[1] To facilitate the linkage to the DEA literature, the general notation, including vector notation, is applied.

[2] An alternative approach was developed by Ebrahimnejad and Tavana (2014). The SBM approach is adopted here since the slack variables are used to calculate efficiency measures (see below).

$$\tau = \min t - \frac{1}{m}\sum_{i=1}^{m}\frac{S_i^-}{x_{io}} \tag{17}$$

$$\text{Subject to} \quad 1 = t + \frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1}\frac{S_r^g}{y_{ro}^g} + \sum_{r=1}^{q_2}\frac{S_r^b}{y_{ro}^b}\right) \tag{18}$$

$$x_0 t = X\boldsymbol{\Lambda} + \boldsymbol{S}^- \tag{19}$$

$$y_0^g t = Y^g\boldsymbol{\Lambda} - \boldsymbol{S}^g \tag{20}$$

$$y_0^b t = Y^b\boldsymbol{\Lambda} + \boldsymbol{S}^b \tag{21}$$

$$\boldsymbol{S}^- \ge 0, \boldsymbol{S}^g \ge 0, \boldsymbol{S}^b \ge 0, \Lambda \ge 0, t \ge 0 \tag{22}$$

Let $(\tau^*, t^*, \boldsymbol{\Lambda}^*, \boldsymbol{S}^{-*}, \boldsymbol{S}^{g*}, \boldsymbol{S}^{b*})$ be the optimal solution of the linear program. Then the optimal solution of the original program (2)–(5) is

$$\rho^* = \tau^*, \lambda^* = \boldsymbol{\Lambda}^*/t^*, s^{-*} = \boldsymbol{S}^{-*}\Big/t^*, s^{g*} = \boldsymbol{S}^g/t^*, s^{b*} = \boldsymbol{S}^{b*}\Big/t^* \tag{23}$$

In the present study, there are four inputs, viz. capital, labor, water, and energy; one desirable output, i.e. industrial output; and three undesirable outputs, viz. waste water discharges, waste gas emissions, and soot emissions. Note that raw materials are also important inputs. However, they are not explicitly included in the DEA since they are merged with capital in the database. Using slack variables, energy efficiency (*EEF*), waste water efficiency (*WWEF*), waste gas efficiency (*WGEF*), soot efficiency (*STEF*), and output efficiency (*OutEF*) measures for each firm can be derived as follows.

The slack variable for energy input is excess energy input. Hence, *EEF* measures how far away a firm is from the energy efficient frontier (Hu and Wang, 2006; Wei et al., 2009). It is defined as:

$$EEF = \frac{AE - ExcessE}{AE} \tag{24}$$

where *AE* is actual energy input and *ExcessE* excess energy input. *AE-ExcessE* is the target energy input that represents the best, i.e. the practical minimum, level of energy input. Actual energy input is a firm's observed energy input. It is always larger than or equal to the target energy input. *EEF* thus is restricted to the interval (0, 1].

The slack variable of pollutant k (k denotes waste water, waste gas or soot in this study) is excess emission of pollutant k. Similar to (24), *EnvEF* is the ratio of the target emission to actual emission (Chang et al., 2013; Tao and Zhang, 2013). For pollutant *k* it reads:

$$EnvEF_k = \frac{AEM_k - ExcessEM_k}{AEM_k} \tag{25}$$

where AEM_k is the actual emission level of pollutant k and $ExcessEM_k$ excess emission level of pollutant k. AEM_k-$ExcessEM_k$ is the target emission of pollutant k that represents the best, practical minimum level of pollutant k. $EnvEF_k$ is restricted to the interval (0, 1]. Based on (25), *WWEF, WGEF*, and *STEF* are derived.

The slack of industrial output represents shortage in desirable output. The target output level is the sum of actual output plus (minimum) shortage in output (*Shortout*). *OutEF* is thus defined as (Gómez-Calvet et al., 2013):

$$OutEF = \frac{AO}{AO + Shortout} \tag{26}$$

where *AO* is actual output level. *AO* + *Shortout* is the target output, i.e. the best, practical maximum level of output. *OutEF* is restricted to the interval (0,1].

2.2. Structural equation model (SEM)

SEM was introduced by Jöreskog (1977) and developed by inter alia Bollen (1989, 1998), Jöreskog and Sörbom (1993), Byrne (2013). Typical for SEM is that it is able to handle latent and observed variables simultaneously within one model framework. A latent variable (theoretical construct) refers to a phenomenon that is supposed to exist but cannot be observed directly. However, it can be measured by means of observed variables (Oud and Folmer (2008) and the references therein). Examples of latent variables in economics are welfare, propensity to consume, expectation.

A SEM consists of two types of sub-models. First, the measurement models for the endogenous and exogenous latent variables:

$$\begin{aligned} y &= \Lambda_y\eta + \varepsilon \\ x &= \Lambda_x\xi + \delta \end{aligned} \tag{27}$$

where *y* is p × 1 vector of endogenous observed variables, *x* a q × 1 vector of exogenous observed variables, η an m × 1 vector of latent endogenous variables, and ξ an n × 1 vector of latent exogenous variables. Λ_y and Λ_x are p × m and q × n matrices of loadings (coefficients) for η and ξ, respectively. ε and δ are p × 1 and q × 1 vectors of the measurement errors, respectively. Note that the two measurement models can be combined into a single measurement model (see inter alia Oud and Folmer, 2008).

The second sub-model is, the structural model that specifies the relationships among the latent variables. It reads:

$$\eta = B\eta + \Gamma\xi + \zeta \tag{28}$$

where *B* is an m × n matrix with β_{ij} representing the relationships among the latent endogenous variables; Γ an m × n matrix giving the effects of the exogenous latent variables on the endogenous latent variables and ζ an m vector of disturbances. For an overview of identification, estimation, testing and model modification, see Jöreskog and Sörbom (2001). Note that it is possible to include an observed variable in the measurement models and the structural model by taking it identical to its corresponding latent variable (loading equal to 1 and measurement error equal to 0). Furthermore, it is possible to include intercepts in the measurement models and in the structural model (Jöreskog and Sörbom, 2001). However, in this paper they are omitted because standardized or beta coefficients are estimated to facilitate comparisons of the effects.

In the structural model, output efficiency (*OutEF*) is an endogenous latent variable that is identical to observed efficiency (as estimated by GDEA) whereas the endogenous latent variable environmental efficiency (*EnvEF*) is measured by the four indicators *EEF, WWEF, WGEF*, and *STEF*, obtained from Equations (24) and (25). Furthermore, a third endogenous latent variable, *Profit*, is included in the structural model that is taken identical to observed *Profit*. It is hypothesized that *Profit* has positive impacts on either or both *OutEF* and *EnvEF*, since a firm with higher profits has more resources to improve efficiency than one with lower profits, ceteris paribus. A reverse relationship, from *EnvEF* and *OutEF* to *Profit*, is also hypothesized. A priori, the signs of the impacts are ambiguous. Either or both may be positive because efficiency implies lower production costs. On the other hand, however, efficiency improvement requires outlays on equipment and training which lower profits, ceteris paribus. As outlined in the Introduction, direct interactions between *EnvEF* and *OutEF* are also hypothesized.

The data set analyzed contains several exogenous variables (controls) that are assumed to impact on the endogenous variables, i.e. the ratio of capital to labor (*Clratio*), age (*Age*), taxes (*Taxes*), size (*Size*), liabilities (*Liabilities*) and sales (*Sales*). Based on theoretical considerations or intuition, the controls are assumed to impact on several of the endogenous variables. Particularly, for *Clratio,* which is the vintage of capital, a high value indicates new, high tech capital and a low value old-fashioned capital (Metcalf, 2008; Wang, 2011; Wu, 2012). *Clratio* thus is expected to directly affect *Profit*, *EnvEF* and *OutEF.* Particularly, a positive impact on environmental efficiency is likely, since new vintage capital tends to be more environmentally friendly, notably more energy efficient (Wu, 2012). *Liabilities,* defined as the total amount of all financial obligations and *Taxes,* defined as taxes and surcharge paid for main operations and made up of business tax, urban construction and maintenance tax, resource use tax, and land appreciation tax, imply additional costs and thus are assumed to reduce profits (Ang et al., 2000; Miller, 2011; Xu et al., 2011; Razak et al., 2011; Sun and Wang, 2014). Both variables are also expected to directly and negatively affect both efficiency variables.[3] *Size*, on the other hand, is likely to have positive impacts on all three endogenous variables because of the ability of large firms to exploit economies of scale, to hire skilled workers and managers, and to adopt advanced technologies (Zheng et al., 2003; Xia and Cheng, 2010; Wang and Hao, 2012; Sun and Wang, 2014; Lin and Long, 2015). In a similar vein, *Sales* is assumed to positively affect *Profit* and the efficiency variables.[4] Finally, since it goes along with knowledge accumulation and learning by doing, *Age* is likely to positively affect *Profit* and *OutEF.* Note that there are also variables that impact on the endogenous variables but are constant for all the firms in the data set. For example, norms and legislation impact on *EnvEF.* Such variables are constant because the affected firms belong to the same jurisdiction (Jiangsu).[5]

Estimation of simultaneous equations models of which all equations contain virtually all controls is infeasible because of identification problems. However, there is little evidence to a priori exclude impacts of the controls on the three endogenous variables. As a way out, a heuristic approach is adopted which involves estimation of several models that differ in terms of restrictions (i.e. zero constraints) on the coefficients in the Γ component of the structural model. Out of the estimated models, the final model is chosen based on theoretical plausibility, significance of the estimated coefficients and overall goodness of fit. Note that the final model thus obtained is preliminary, especially regarding the relationships between the controls and the endogenous variables since it has not been estimated and tested in previous studies and thus it is based on the present data set only.

In terms of Equation (27) and (28), the SEM efficiency model outlined above reads as follows:

Measurement model of the endogenous latent variables:

$$\begin{bmatrix} EEF \\ WWEF \\ WGEF \\ STEF \\ OutEF \\ Profit \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ \lambda^y_{21} & 0 & 0 \\ \lambda^y_{31} & 0 & 0 \\ \lambda^y_{41} & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} EnvEF \\ OutEF \\ Profit \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ 0 \\ 0 \end{bmatrix} \tag{29}$$

Measurement model of the exogenous variables:

$$\begin{bmatrix} Clratio \\ Age \\ Taxes \\ Size \\ Liabilities \\ Sales \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} Clratio \\ Age \\ Taxes \\ Size \\ Liabilities \\ Sales \end{bmatrix} \tag{30}$$

Structural model:

$$\begin{aligned} \begin{bmatrix} EnvEF \\ OutEF \\ Profit \end{bmatrix} &= \begin{bmatrix} 0 & 0 & \beta_{1,3} \\ \beta_{2,1} & 0 & \beta_{2,3} \\ \beta_{3,1} & \beta_{3,2} & 0 \end{bmatrix} \begin{bmatrix} EnvEF \\ OutEF \\ Profit \end{bmatrix} \\ &+ \begin{bmatrix} \gamma_{1,1} & 0 & 0 & 0 & 0 & 0 \\ 0 & \gamma_{1,2} & \gamma_{2,3} & \gamma_{2,4} & 0 & 0 \\ 0 & 0 & 0 & 0 & \gamma_{3,5} & \gamma_{3,6} \end{bmatrix} \\ &\times \begin{bmatrix} Clratio \\ Age \\ Taxes \\ Size \\ Liabilities \\ Sales \end{bmatrix} + \begin{bmatrix} \varsigma_1 \\ \varsigma_2 \\ \varsigma_3 \end{bmatrix} \end{aligned} \tag{31}$$

Note that to render the model identified, the coefficient of *EEF* is fixed at 1 in Equation (29) thus assigning a measurement scale to the unobserved latent variable *EnvEF.* Furthermore, in Equation (30) the latent variables are equal to their observed indicators. As a result, the error terms are fixed at 0.

3. Study area and data sources

The data analyzed relate to China's Jiangsu Province (hereafter Jiangsu) in 2009. Jiangsu had a population of 79 million (in 2011) that accounted for about 6% of China's total. It is located in the Yangtze River Delta and has an area of 102600 square kilometers, about 1.1% of the entire nation's (Long and Ng, 2001; Jiangsu Statistical Yearbook, 2012).

Jiangsu is one of the economically most developed provinces and has a high economic growth rate. Its Gross Provincial Product (GPP) has been growing from 25 billion Yuan in 1978–4911 billion Yuan in 2011, with an average annual nominal growth rate of 17.4% and a real annual growth rate of 12.3%. Jiangsu has played an important role in China's economic development (Zhang and Huang, 2012). Its Gross Provincial Product (GPP) accounted for almost 10% of China's GDP in 2011 (NBS, 2012). Among 31 Chinese Provinces (excluding Taiwan, Hongkong, Macau), its GPP ranked second, only behind Guangdong Province. However, its rapid

[3] Note that *Taxes* do not necessarily hamper *Efficiency* via investments because investments depend on many factors, including expected sales, the level of taxation, depreciation rules, dividend policy, investment tax-shield, firm size, debt service, etc. The objective of this paper is not analysis of the conditions under which *Taxes* hamper investments or not. Such an analysis would be far beyond the scope of the paper. Moreover, the data is not available. We merely estimate the impact of *Taxes* on efficiency. Also note that *Liabilities* do not necessarily reduce profit and resources. The impact depends on a variety of circumstances. As in the case of *Taxes*, we do not analyze the conditions under which *Liabilities* hamper *Profit* or not. We merely estimate the impact of *Liabilities* on *Profit*.

[4] Note that there could be a cycle from *Sales* to *Profit* to *Efficiency* and back to *Sales*, e.g. via price reduction. However, the allocation of the returns to efficiency improvement is multifaceted. The returns could be used for expansion, to raise wages and so on. The interesting research question of the allocation of efficiency gains is beyond the scope of the paper, inter alia, because of identification problems. Therefore, we defined *Sales* as an exogenous variable.

[5] Note that environmental regulations may have different impacts depending, for instance, on location and size of the firm but also on local circumstances such as corruption. Unfortunately, there is no information in the data set on these variables, except for *Size* which is included in the model as exogenous variable. Therefore, we can merely assume that omitted variables like location and corruption (captured by the error term) are not, or only slightly, correlated with the explanatory variables. The plausibility of the estimated coefficients lends support to this assumption.

Table 1
Input and output variables of the GDEA.

Variable	Definition	Unit	Mean	S.D.	Min.	Max.
Capital	Value of fixed assets	Million Yuan	70.38	361.28	0.63	4170.39
Labor	Number of employees	Capita	514.25	1314.71	30.00	14300.00
Energy	Coal consumption	Tons	6775.10	16876.55	97.00	146515.00
Water	Water use	Thousand Tons	635.00	900.75	10.00	8724.47
Output	Industrial output value	Million Yuan	285.23	1389.36	6.70	16005.16
Wastewater	Volume of waste water discharges	Thousand Tons	480.78	690.57	0.80	6979.58
Wastegas	Volume of waste gas emissions	Million Cubic meters	70.00	169.68	1.20	1465.15
Soot	Volume of soot emissions	Tons	37.43	64.34	0.75	455.00

Note: S.D. denotes standard deviation, Min. minimum and Max. maximum.
Source: Environmental Protection Department of Jiangsu Province and Chinese Industrial Enterprises Database

economic growth has been accompanied by substantial energy consumption.

Jiangsu has been suffering from energy shortages for years. In 2000 it produced 20 million tons SCE only, but consumed 86 million tons, resulting in a deficiency of 66 million tons. In 2011 Jiangsu's energy consumption of 276 million tons SCE even more exceeded its energy supply of 26 million tons SCE. The ratio of energy production to energy consumption sharply declined from 23% in 2000 to less than 10% in 2011, indicating a rapidly widening energy gap during the past decade. The main reason is that Jiangsu lacks energy resources. Specifically, it is endowed with only 0.5% of China's total coal reserves, 1.05% of its oil reserves and 0.06% of its natural gas reserves. It also lacks hydro power because it is plain. It is relatively rich in wind power, though. Jiangsu thus heavily depends on imports of energy from energy-rich provinces.

Jiangsu heavily depends on the use of coal (more than 70% in 2011) which has been the main cause of environmental degradation. In 2011, SO_2 emissions totaled 1.1 million tons, NO_x emissions 1.5 million tons, and smoke and dust 0.5 million tons. These pollutants have seriously deteriorated Jiangsu's environment.

Energy efficiency improvement has played a major role in reducing energy consumption and emissions in Jiangsu. Energy intensity has substantially decreased, from 3.9 tons SCE per 10,000 Yuan in 1990 to 1.3 in 2010 (in 1990 constant prices). However, it still lags behind developed countries (Hong et al., 2013) indicating that Jiangsu has a huge potential to improve its energy efficiency. In the 11th Five-Year Plan (2006–2010), a specific target of improving energy efficiency by 20% was assigned to Jiangsu. By the end of 2010, it had successfully reduced energy consumption per unit of GPP by 20.5% (Duan and Hu, 2014). No targets were set for the main pollutants, however.

The data set includes 137 firms, classified into 3 manufacturing sectors at 2-digit level, based on the "Classification and code standard of national economy industry" released by the National Bureau of Statistics of China (source: http://www.stats.gov.cn/tjsj/tjbz/hyflbz/). The 3 sectors, viz. "manufacturing of textile", "manufacturing of wearing apparel and accessories", and "manufacturing of leather, fur, feather and related products and footwear" are grouped into one single group, viz. textile, according to similarities between products. Data is available for 2009 only. Data for capital, labor, and industrial output value is obtained from the Chinese Industrial Enterprises Database which is not publicly available.[6] Data for water use, energy consumption, waste water discharges, waste gas emissions, and soot emissions is obtained from the Environmental Protection Department of Jiangsu. Table 1 presents the definitions, units of measurement, and descriptive statistics (mean, standard deviation (SD), minimum (Min) and maximum (Max)) of the input variables, and of the desirable and undesirable output variables of the GDEA. Note that due to data limitations the only energy source considered is coal. So, the energy efficiency indicator below is in fact a "coal indicator". This limitation affects the environmental only marginally because coal is by far the most important energy source in the Jiangsu textile industry.

Data for the controls in the SEM is from the Chinese Industrial Enterprises Database. Table 2 presents their definitions, units of measurement, and descriptive statistics.

4. Empirical results

Table 3 presents descriptive statistics of the output of the GDEA (Equations (17)–(23), i.e. the efficiency indices *GEF*, *EEF*, *WWEF*, *WGEF*, *STEF*, and *OutEF*. The table shows that generalized efficiency has the lowest mean among all efficiency measures. This is because it is a multi-factor efficiency measure which combines inputs and output leading to the low generalized efficiency score. It indicates substantial potential to save inputs or to improve output.

The means of the single factor efficiency measures *EEF*, *WWEF*, *WGEF* and *STEF* range from 0.2896 to 0.3874 and are much lower than that of *OutEF*. Note also that the means of the environmental efficiency indicators *EEF*, *WGEF* and *STEF* are very close which is due to the fact that they are all highly related to coal combustion.

The SEM is estimated by means of the software package LISREL 8 (Jöreskog and Sörbom, 2001). The results are presented in Tables 4–6. The Initial Model in Table 4 includes all relevant variables in the data set (briefly discussed in Section 2). However, the variable *Age* turned out to be highly insignificant in all models and was deleted from the analysis. The resulting model is the Final Model. Table 4 presents overall-goodness–of-fit measures of the Initial (including *Age*) and of the Final Model (without *Age*): the χ^2/df, the root mean square error of approximation (RMSEA), the goodness of fit index (GFI), the adjusted goodness of fit index (AGFI), the comparative fit index (CFI), and the normed fit index (NFI) (Note that it is possible to apply a χ^2 based test. However, the test is highly sensitive to deviation from normality and hampered by small sample size (Jöreskog and Sörbom (2001), Hox and Bechger (1998)). Under those conditions the fit measures χ^2/df and RMSEA are more appropriate.) From Table 4 it follows that the goodness of fit statistics of both the Initial and Final Models meet their critical values, although the χ^2/df and the RMSEA of the former are slightly better than those of the latter. On the basis of these results the Final Model is now discussed.

The modification indices of the structural model presented in Table 5 give hints about incorrectly fixed or constrained parameters. More precisely, a modification index is the predicted decrease in χ^2, if a single fixed parameter or equality constrained is relaxed and the model is re-estimated (Jöreskog and Sörbom, 2001). As a rule of thumb, a modification index larger than 7 is an indication of an incorrectly fixed or constrained parameter. Table 5 shows that none of the fixed parameters exceeds the critical value which

[6] The data was made available to the third co-author for the present study.

Table 2
The SEM control variables.

Variable	Definition	Unit	Mean	S.D.	Min.	Max.
Clratio	The ratio of capital to labor	Million Yuan/capita	0.099	0.076	0.005	0.555
Age	Age of the firm	Years	15.956	11.369	5.000	54.000
Taxes	The ratio of taxes and surcharge paid for main operations to total profit		0.339	0.352	0.000	1.984
Size	Total assets	Billion Yuan	0.193	0.952	0.003	11.035
Liabilities	Total liabilities	Million Yuan	274.268	1361.187	7.186	15783.505
Sales	Gross industrial products sales	Million Yuan	111.180	482.608	0.455	5538.57
Profit	The ratio of total profits to total sales in 2008	Million Yuan	0.327	0.060	−0.253	0.297

Note: S.D. denotes standard deviation, Min. minimum and Max. maximum.
Source: Chinese Industrial Enterprises Database

Table 3
Descriptive statistics of the efficiency measures.

Efficiency measure	Mean	SD	Min
Generalized/overall efficiency (*GEF*)	0.2902	0.3416	0.0292
Energy efficiency (*EEF*)	0.3934	0.3391	0.0270
WWEF (waste water efficiency)	0.2896	0.3639	0.0124
WGEF (waste gas efficiency)	0.3832	0.3320	0.0185
STEF (soot efficiency)	0.3874	0.3606	0.0080
Output efficiency (*OutEF*)	0.8189	0.2688	0.1809

Table 4
SEM goodness-of-fit statistics.

	χ^2/df	RMSEA	GFI	AGFI	CFI	NFI
Initial Model	1.639	0.064	0.94	0.86	0.98	0.95
Final Model	1.806	0.073	0.93	0.86	0.98	0.96
Cut off value	<3	<0.08	>0.90	>0.80	>0.90	>0.90

Note: For more details about cut off values see Hooper et al. (2008).

Table 5
Matrix of modification indices of the SEM.

	EnvEF	*OutEF*	*Profit*
EnvEF	–	–	–
OutEF	0.04	–	–
Profit	–	–	–
Clratio	–	0.00	0.08
Age			
Taxes	3.22	–	0.42
Size	0.58	–	0.68
Liabilities	2.48	0.15	–
Sales	0.79	0.15	–

Note: critical value: 7.

Table 6
The SEM measurement model.

Latent variable	Indicator	Coefficient	R^2
EnvEF	*EEF*	0.33 –	0.94
	WWEF	0.31*** (0.05) *17.46*	0.73
	WGEF	0.33*** (0.03) *35.43*	0.97
	STEF	0.33*** (0.05) *21.54*	0.82
OutEF	*OutEF*	0.27 –	1.00
Profit	*Profit*	0.06 –	1.00

Notes: coefficients are completely standardized coefficients; standard errors within brackets; t-values in italics; ***: p < .01.

supports the parameter configuration (i.e. the fixed (at 0) and free, estimated parameters).

Table 6 presents the estimated measurement models. Before discussing the results, note that the estimated coefficients are standardized (beta) coefficients. They are directly comparable since a beta coefficient represents the standard deviation change in an endogenous variable due to a standard deviation change in an explanatory variable (Wooldridge, 2012). Note that standardization also affects the coefficients of the indicators *EEF*, *OutEF*, and *Profit* that originally were fixed at 1.

Table 6 shows that all factor loadings of the indicators of the latent variable *EnvEF* are highly significant and that their reliabilities (R^2) are larger than the minimum level of 0.20 recommended by Jöreskog and Sörbom (2001). Hence, *EnvEF* is measured well. Note also that the loadings of the indicators are virtually equal.

The structural model is presented in Table 7 and Fig. 1. Table 7 shows that all the coefficients in the structural model are significant at 10%. Moreover, the R-squared of the three equations are quite high. Below the two efficiency sub-models are first discussed, next the profit sub-model.

Profit has a positive impact on *EnvEF*, indicating that profit induces *EnvEF*. *Clratio* on the other hand negatively and significantly impacts on *EnvEF*. A possible explanation is that the textile industry still is labor-intensive rather than capital and energy-intensive. A

Table 7
The SEM structural model.

Variable	*EnvEF*	*OutEF*	*Profit*
EnvEF	–	0.62*** (0.10) *5.18*	−0.98*** (0.06) −2.82
OutEF	–		−1.47*** (0.10) *−3.46*
Profit	1.18*** (1.81) 3.56	0.30*** (0.52) *2.56*	–
Clratio	−0.23* (0.53) *−1.88*	–	–
Taxes	–	−0.26*** (0.06) *−3.26*	–
Size	–	0.48*** (0.04) *6.21*	–
Liabilities	–	–	−1.19*** (0.03) *−3.56*
Sales	–	–	2.37*** (0.06) *4.34*
R^2	0.69	0.73	0.79

Notes: coefficients are completely standardized coefficients; standard errors within brackets; t-values in italics; *: p < .10, **: p < .05, ***: p < .01.

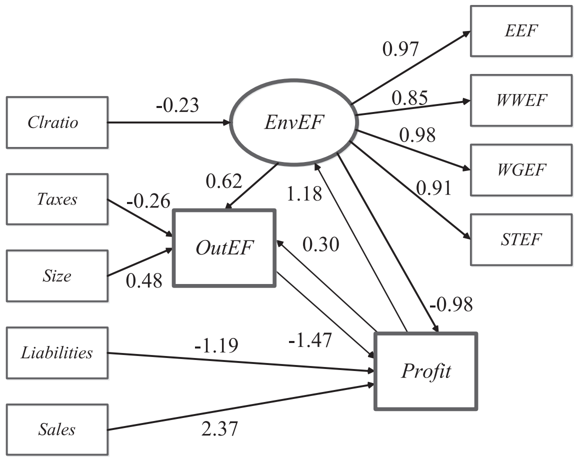

Fig. 1. The path diagram. Note: The latent variable *EnvEF* is in the ellips; observed variables are in rectangles; an arrow indicates a direct influence; measurement errors and structural errors have been omitted.

high capital labor ratio might imply excess investment in capital and equipment resulting in higher than optimal energy use which impairs *EnvEF*. Note that the estimated impact of *OutEF* on *EnvEF* was virtually zero and highly insignificant. It was therefore fixed at 0.

From the output efficiency sub-model it follows that *EnvEF* has a positive impact on *OutEF*, indicating that, ceteris paribus, an environmentally friendly firm tends to save costs via reduction of inputs, notably energy. The positive impact of *Profit* on *OutEF* implies that a high profit firm can save on costs e.g. via installment of efficient capital thus improving *OutEF*. *Taxes* negatively impact on *OutEF* indicating that a heavy tax burden impairs a firm's *OutEF*. *Size* has a positive impact on *OutEF* implying that a large firm tends to exploit economies of scale, which benefits *OutEF*.

The profit sub-model shows that *EnvEF and OutEF* negatively impact on *Profit* indicating that both kinds of efficiency improvement absorb resources at the expense of *Profit*. *Liabilities* also have a negative impact on *Profit*. *Sales* on the other hand positively impact on *Profit*, indicating that a firm with high turnover tends to have high profits.

Table 8 presents the total effects of all explanatory variables on *EnvEF*, *OutEF* and *Profit*. The total effect of an explanatory variable on an endogenous variable is the sum of its direct and indirect effects on that variable (Jöreskog and Sörbom, 2001). The former is given by the coefficient in the structural model (Table 7). The latter is the effect of the variable on the endogenous variable via intervening endogenous variables. Note that an endogenous variable can have an effect on itself via reciprocal or circular paths via other endogenous variables. The table shows that *OutEF* (−0.47), *Liabilities* (−0.38) and *Size* (−0.23) have significant and negative total effects on *EnvEF* while *EnvEF* also has a negative effect on itself via *Profit*. *Clratio* has a marginally significant, negative total effect (−0.09) on *EnvEF*. There is no direct effect of *Taxes* on *EnvEF*. However, its negative effect on *OutEF* (−0.26) has a negative impact on *Profit* (−1.47) which in its turn has a positive impact on *EnvEF* (1.18*)*. The effect o*f Taxes* on *OutEF* along this path is positive: 0.45. This effect is reduced by −0.33 which is the sum of the effects of the loop among *EnvEF* and *Profit*. Thus, its total effect on *EnvEF* amounts to 0.12. *Sales* (0.76) has a significant, positive total effect on *EnvEF* via *Profit,* although it has no direct effect. The significant total effects of *Size* (*-0.23*) and *Liabilities* (−0.38) also arise from indirect effects, i.e. via the intervening endogenous variables *OutEF* and *Profit.*

The variables with significant, positive total effects on *OutEF* are *EnvEF* (0.09), *Profit* (0.28), *Size* (0.28) and *Sales* (0.67). Note that there is no direct effect of *Sales* on *OutEF*. However, it has a positive total effect via *Profit*. *Taxes* (−0.15) and *Liabilities* (−0.33) have negative total effects on *OutEF* while it also has a negative effect on itself via *Profit*. The negative total effect of *Liabilities* (−0.33) comes from the indirect effect via *Profit*.

Table 8
Standardized total effects of the SEM.

	EnvEF	*OutEF*	*Profit*
EnvEF	−0.61***	0.09*	−0.51***
	(0.14)	(0.04)	(0.01)
	−4.49	*1.90*	*−10.22*
OutEF	−0.47***	−0.41***	−0.40***
	(0.09)	(0.10)	(0.02)
	−6.34	*−4.04*	*−4.89*
Profit	0.32***	0.28***	−0.73***
	(0.32)	(0.23)	(0.10)
	5.44	*5.48*	*−7.50*
Clratio	−0.09	−0.02	0.12*
	(0.24)	(0.05)	(0.05)
	−1.61	*−1.35*	*1.87*
Taxes	0.12***	−0.15***	0.10***
	(0.04)	(0.04)	(0.01)
	2.86	*−3.04*	*2.67*
Size	−0.23***	0.28***	−0.19***
	(0.03)	(0.03)	(0.01)
	−4.41	*4.02*	*−3.98*
Liabilities	−0.38***	−0.33***	−0.32***
	(0.06)	(0.03)	(0.01)
	−3.74	*−4.75*	*−3.61*
Sales	0.76***	0.67***	0.64***
	(0.07)	(0.05)	(0.01)
	6.03	*6.29*	*5.00*

Notes: standard errors within brackets; t-values in italics; *:p < .10, **:p < .05, ***:p < .01.

The variables with negative total effects on *Profit* are *EnvEF* (−0.51), *OutEF* (−0.40), *Liabilities* (−0.32) and *Size* (−0.19) while *Profit* (−0.73) also have a negative effect on itself via *EnvEF* and *OutEF*. The negative total effects of the first two variables are smaller than their direct effects because of indirect effects (the negative relationship between *EnvEF* and *OutEF* leading to a positive impact on *Profit*). *Clratio* has no direct effect on *Profit*. However, it has a significant and positive total effect on *Profit* (0.32) via *EnvEF*. *Taxes* have no direct effect on *Profit*, either. However, their positive total effect (0.10) on *Profit* arises from the indirect effect via *OutEF*. In a similar vein, *Size* (−0.19) indirectly impacts on *Profit* via *OutEF*, although it has no direct effect, either. The total effect of *Sales* (0.64) on *Profit* is smaller than its direct effect because *Profit* has a negative effect on the efficiency variables which feedback on *Profit*.

5. Conclusion and policy recommendations

The main purpose of this paper was the analysis of the interaction between environmental efficiency and output efficiency, particularly, whether they reinforce each other or compete with each other. For this purpose, a data set of 137 firms in the textile industry in China's Jiangsu Province was analyzed. As a first step, efficiency measures for energy (*EEF*), waste water (*WWEF*), waste gas (*WGEF*), soot (*STEF*), and output (*OutEF*) were calculated by means of Generalized DEA (GDEA) taking capital, labor, water, and energy as inputs, industrial output value as desirable output, and waste water discharges, waste gas emissions, and soot emissions as undesirable outputs. In the second-stage analysis, the interaction between the two efficiency measures was analyzed by way of a structural equation model with latent variables (SEM). The input into the SEM was obtained from the GDEA. Environmental efficiency (*EnvEF*) was measured by the four environmental indicators, and output efficiency (*OutEF*) was taken identical to observed *OutEF*. *Profit* was also included in the SEM as an endogenous variable.

The main findings of the analysis are the following. Environmental efficiency has a negative impact on profit while profit has a positive impact on environmental efficiency. A similar relationship holds for output efficiency and profit: output efficiency reduces profit while profit induces output efficiency. The rationale is that efficiency improvement requires resources which depresses profit. Furthermore, environmental efficiency positively affects output efficiency but there is no reverse effect. Regarding the control variables, the capital labor ratio negatively and significantly affects environmental efficiency, taxes output efficiency and liabilities profit. Firm size on the other hand has a positive impact on output efficiency and sales on profit.

The finding that environmental efficiency induces output efficiency has implications for environmental policy, at least in sectors like the textile sector in Jiangsu. First, the results indicate that although environmental policy aimed at improving environmental efficiency, particularly energy efficiency, depresses profit, it stimulates output efficiency. This is an indication for policymakers to continue the development and implementation of environmental policy aimed at improving environmental and energy efficiency. The rationale is that such a policy is not only desirable from an environmental and energy policy point of view, but also from a broader economic perspective because rising production costs have increasingly started hampering exports (Singh and Mahmood, 2014). This is in line with IEA (2014) which shows that investment in energy efficiency may have several benefits to firms. Evidently, it directly reduces energy demand and associated costs. Moreover, it may facilitate the achievement of some objectives, for example, boosting industrial productivity. Further stimulation of environmental and energy efficiency also fits into the national and 11th Five Year Plan (2006–2010) and its follow up of the 12th Five Year Plan (2011–2015). It follows that investment in energy efficiency leads to a win–win situation which may facilitate the adoption of such environmental policy by firms. A possible energy efficiency stimulating policy is a tax swap of general taxes for an energy tax. As shown in the analysis taxes impair a firm's output efficiency. An energy tax on the other hand is a stimulus to reduce energy use. A tax swap is thus likely to improve both output efficiency and energy efficiency.

The analysis presented in this study relates to a small sector in one province for one year only. Further analysis of other sectors in other regions and over longer time spans is needed. For that purpose the methodology presented in this paper consisting of generalized DEA and structural equation modeling with latent variables, is promising. Besides, this study relates to China. However, environmental degradation, energy shortage and energy efficiency are also major issues in other developing countries like India, Pakistan, Bangladesh, Indonesia and several African and Latin American countries. The analyses could be readily applied in other (developing) countries.

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