Chapter 5 Interaction between output efficiency and environmental efficiency: Evidence from the textile industry in Jiangsu Province, China

Abstract: 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 with respect to whether they reinforce or compete with each other - based on a data set of 137 textile-industry firms in China’s Jiangsu province. In the first stage of the analysis, generalized data envelopment analysis is applied to calculate efficiency measures of energy, wastewater, waste gas, soot, and output efficiency. This stage of the analysis takes capital, labor, water, and energy as inputs; industrial output value as the desirable output; and wastewater discharges, waste gas and soot emissions as undesirable outputs. In the second stage of the 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, also considering the endogenous variable profit. The main outcomes of the structural equation model are as follows. First, environmental efficiency negatively impacts profit, whereas profit positively impacts environmental efficiency. In a similar vein, output efficiency is found to depress profit, whereas profit increases output efficiency. Third, environmental efficiency has a positive impact on output efficiency, whereas output efficiency has no impact on environmental efficiency. Fourth, taxes impair a firm’s output efficiency. From the findings, it follows that substituting an energy tax for general taxes is likely to improve both output efficiency and energy efficiency. The latter outcome implies a win-win situation that will facilitate the further implementation and adoption of environmental policy. Finally, the paper illustrates the applicability of structural equation modeling in efficiency analysis.

Keywords: Energy efficiency; Output efficiency; Environmental efficiency; Data envelopment analysis (DEA); Structural equation model (SEM); Jiangsu Province
5.1 Introduction

Environmental efficiency improvement has played a crucial role in both the theory and the practice of stimulating clean production. Nevertheless, the determinants and impacts of environmental efficiency are not fully understood, particularly with respect to the relationship between environmental efficiency and output efficiency. Environmental efficiency (especially energy efficiency) has two possible effects on output efficiency. First, it has a positive effect in that an environmentally friendly/energy-efficient firm has lower energy costs, which, ceteris paribus, improves its output efficiency. Second, and conversely, improving environmental efficiency implies opportunity costs in that resources used to improve environmental efficiency could have been used to improve output efficiency. Moreover, output efficiency may impact environmental efficiency in one of two ways. First, it has a positive effect in that ceteris paribus, output-efficient firms have more resources than output-inefficient ones to improve environmental efficiency. Second, output efficiency may have been achieved at the expense of environmental efficiency which would show up as a negative relationship.

Environmental efficiency, most notably energy efficiency, has played a crucial role in China. Its unprecedented economic growth has been accompanied by a dramatic increase in energy consumption, which has risen more than six fold over the past 35 years, from 571 million tons standard coal equivalent (SCE) in 1978 to 3750 million tons SCE 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, China consumed approximately 12.12% of the world’s oil, nearly 5% of the world’s natural gas, approximately 50% of the world’s coal, and 24% of the world’s hydropower. Moreover, it has become one of the world’s largest energy producers (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: energy shortage and environmental degradation (Song et al., 2011; Meng et al., 2013; Lin and Ouyang, 2014). With respect to the first challenge, China has been suffering from a rapidly increasing energy gap for more than two decades. In 2013, it suffered 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 oil. In 2013, imported oil accounted for nearly 70% of China’s total oil consumption (NBS, 2014).

With respect to the second challenge, China has experienced increased environmental degradation caused by emissions caused by fossil-fuel combustion (Yong and Oberheittmann, 2008; Wang et al., 2012). In 2012, China’s total SO₂ emissions were 21.2 million tons, its total NOₓ were 23.4 million tons, its total smoke and dust emissions were 12.4 million tons, and its total CO₂ emissions were 9.9 billion tons (NBS, 2013; Netherlands Environmental Assessment Agency, 2013). SOₓ and NOₓ, which are the main causes of acid rain, have affected approximately 300 cities in China (Zhang et al., 2011). In 2008, economic losses caused by fossil-fuel combustion-based pollution accounted for 3.9% of China’s gross domestic product (GDP) (Li et al., 2013). Coal combustion is the primary source of this pollution: 90% of SOₓ, 67% of NOₓ and 70% of China’s total CO₂ emissions results from coal combustion (Fang and Zeng, 2007).

In China, improvements in energy efficiency have played a crucial role in addressing both energy shortages and environmental degradation (Tanaka, 2008; Andrews-Speed, 2009). Energy-efficiency improvement has long been regarded as a top priority by the Chinese central government. In its 11th Five-Year Plan (2006–2010), the Chinese government for the first time launched a nationwide campaign to improve 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 considers only one output. Conversely, DEA, proposed by Charnes et al. (1978), is a non-parametric (optimization) approach that can address a system of multiple outputs and inputs (Wu, 2014). Moreover, it does not require functional specifications between the inputs and the outputs (Seiford and Thrall, 1990; Shi et al., 2010; Wu, 2014). Another advantage of DEA is that it only requires information about 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) have used DEA to measure the energy efficiency of 29 Chinese provinces from 1997-2006. Wei et al. have also found that the eastern region had the highest energy-efficiency score, the western region had the lowest score and the central region’s score was in between. Another application is that of Martínez (2011), who has applied DEA to measure energy-efficiency development in non-energy-intensive sectors in Germany and Colombia from 1998-2005. Martínez has found that the average energy efficiency scores were similar in both countries. Third, Blomberg et al. (2012) have evaluated the electricity efficiency of more than 30 pulp and paper mills for the years 1995, 2000 and 2005 using DEA. They have observed that the electricity-efficiency gap among the mills studied was relatively stable over time.

Conventional DEA models proceed on the assumption that inputs are minimized and economic output is maximized in the production process (Scheel, 2001; Jahanshahloo et al., 2005). This assumption ignores that production leads to both desirable and undesirable outputs, particularly emissions (Färe and Grosskopf, 2004; Färe et al., 2005; Zhou et al., 2007; Liu et al., 2010; Wang et al., 2012; Wang et al., 2013; Pérez-Calderón et al., 2011, Wu, 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., 2014; Song et al., 2012). DEA that takes both goods and bads into account is denoted here as generalized DEA (GDEA).

The basic notion of incorporating both positive and negative outputs (e.g., pollutants) in the DEA framework originates from Pittman’s (1983) seminal work. In recent years, this approach has gained popularity in the field of energy-efficiency analysis. For example, Sözen et al. (2010), in their generalized efficiency analysis of 15 thermal power plants in Turkey, have taken thermal efficiency, operational time, and fuel cost as inputs; electricity as the desirable output; and CO₂, SO₂, N₂O, CH₄, CO, NOₓ, and non-methane volatile organic compound (NMVOC) emissions as undesirable outputs. They have found a large efficiency gap across the 15 thermal power plants. Another application is Sueyoshi and Goto (2014), who have used three inputs, - viz., assets, employees and energy - in their generalized efficiency analysis of 31 Japanese chemical and pharmaceutical firms. They have taken sales as the desirable output and greenhouse gas emissions and waste discharges as undesirable outputs. They have found that the pharmaceutical firms outperformed the chemical firms.

Some Chinese studies have also considered undesirable outputs. For example, Shi et al. (2010) have measured the industrial energy efficiency of 28 provinces from 2000–2006, taking assets, labor, and energy as inputs; industrial added value as the desirable output; and waste gas as the undesirable output. They have found that the eastern region had the highest average energy efficiency score, followed by the central and western regions. Wang et al. (2012) have used capital stock, labor, coal, oil, and natural gas as inputs; gross provincial product as the desirable output; and CO₂ and SO₂ as undesirable outputs to measure the energy efficiency of China’s 30 provinces from 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) have reported energy-efficiency scores for 29 Chinese provinces from 2000–2008 and from 1991–2001. They have taken gross provincial product as the desirable output; capital stock, labor and energy
as inputs; and CO$_2$ emissions and SO$_2$ emissions as undesirable outputs. The latter study has taken wastewater, 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 the firm level in China. An exception is He et al. (2013), who have evaluated the energy efficiency of 50 large iron and steel enterprises, taking three undesirable outputs—viz., waste gas, wastewater and solid waste—into consideration. They have found an average energy efficiency of only 0.611. We have not been able to find empirical efficiency studies for small and medium-sized firms in China, probably due to data limitations.

The existing literature has focused exclusively on the calculation of efficiency and has ignored the possible interaction between desirable output efficiency and environmental efficiency. This paper intends to fill the 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 using 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 5.2 briefly summarizes GDEA and SEM. Section 5.3 describes the study area and data sources, and section 5.4 presents the empirical results. Section 5.5 concludes and presents policy recommendations.

### 5.2 Methods

Generalized data envelopment analysis (GDEA) is introduced in section 5.2.1. In section 5.4, GDEA will be applied to calculate indices of energy efficiency ($EEF$), wastewater efficiency ($WWEF$), waste-gas efficiency ($WGEF$), soot efficiency ($STEF$),


and output efficiency (\(OutEF\)) for each firm. The outputs of the GDEA (the four environmental measures) are inputs into the SEM, which will be applied to analyze the interaction between output efficiency and environmental efficiency, as measured by the above four environmental indices. The SEM is summarized in section 5.2.2.

### 5.2.1 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: \(x \in \mathbb{R}^m\) (inputs), \(y^g \in \mathbb{R}^q\) (desirable or good output), and \(y^b \in \mathbb{R}^q\) (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 follows:

\[
X = [x_1, \ldots, x_n] \in \mathbb{R}^{m \times n}, \quad Y^g = [y^g_1, \ldots, y^g_n] \in \mathbb{R}^{q_1 \times n}, \text{ and } Y^b = [y^b_1, \ldots, y^b_n] \in \mathbb{R}^{q_2 \times n}.
\]

It is assumed that all inputs and outputs are non-negative.

The production possibility set \((P)\) is defined as follows:

\[
P = \{(x, y^g, y^b) \mid x \geq X\lambda, y^g \leq Y^g\lambda, y^b \leq Y^b\lambda, \lambda \geq 0\} \tag{5.1}
\]

where \(\lambda\) 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 considered first\(^{21}\). The slack-based measure (SBM) approach first proposed by Tone (1997, 2001) is adopted and formulated as the following minimization program\(^{22}\):

\(^{21}\) To facilitate the linkage to the DEA literature, the general notation, including the vector notation, is applied.

\(^{22}\) An alternative approach has been developed by Ebrahimnejad and Tavana (2014). The SBM approach is adopted here because the slack variables are used to calculate the efficiency measures (see below).
\[
\min \rho = \frac{1 - \frac{1}{m} \sum_{i=1}^{m} s_i^-}{1 + \frac{1}{q} \sum_{r=1}^{q} s_r^+}
\]

(5.2)

Subject to
\[
x_0 = X \lambda + s^-
\]

(5.3)

\[
y_0 = Y \lambda - s^+
\]

(5.4)

\[
s^- \geq 0, s^+ \geq 0, \lambda \geq 0
\]

(5.5)

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

To take undesirable outputs into account, system (5.2)-(5.5) can be modified to evaluate DMU \((x_0, y_o^g, y_o^b)\) as follows (Li et al., 2014):

\[
\rho = \min \frac{1 - \frac{1}{m} \sum_{i=1}^{m} s_i^-}{1 + \frac{1}{q_1 + q_2} \left( \sum_{r=1}^{q_1} s_r^g + \sum_{r=1}^{q_2} s_r^b \right)}
\]

(5.6)

Subject to
\[
x_0 = X \lambda + s^-
\]

(5.7)

\[
y_o^g = Y^g \lambda - s^g
\]

(5.8)

\[
y_o^b = Y^b \lambda + s^b
\]

(5.9)

\[
s^- \geq 0, s^g \geq 0, s^b \geq 0, \lambda \geq 0
\]

(5.10)

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

System (5.6)-(5.10) comprises a nonlinear program that can be transformed into a linear program (LP) using the Charnes-Cooper transformation (Charnes and Cooper, 1962; Li et al., 2013; Chang et al., 2013; Li et al., 2014). The transformation is as
follows. First, following Charnes and Cooper (1962), a scalar variable $t$ ($t>0$) is included in system (5.6)-(5.10), which multiplies both the denominator and the numerator of (5.6) and thus does not change $\rho$. Furthermore, the denominator is made equal to 1 by adjusting $t$, which is then specified as a constraint ((5.12) below). The objective, then, is to minimize the numerator. System (5.6)-(5.10) now reads as follows (Tone, 2001):

$$
\tau = \min t - \frac{1}{m} \sum_{i=1}^{m} \frac{tS^-}{x_{i0}} \tag{5.11}
$$

Subject to

$$
1 = t + \frac{1}{q_1 + q_2} \left( \sum_{i=1}^{q_1} \frac{tS^g}{y_{i0}} + \sum_{i=1}^{q_2} \frac{tS^b}{y_{i0}} \right) \tag{5.12}
$$

$$
x_0 = X\lambda + S^- \tag{5.13}
$$

$$
y_0^g = Y^g\lambda - S^g \tag{5.14}
$$

$$
y_0^b = Y^b\lambda + S^b \tag{5.15}
$$

$$
S^- \geq 0, S^g \geq 0, S^b \geq 0, \lambda \geq 0 \tag{5.16}
$$

System (5.11)-(5.16) contains the nonlinear term $ts$. This system 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 (5.11)-(5.16) becomes the following linear program (Tone, 2001):

$$
\tau = \min t - \frac{1}{m} \sum_{i=1}^{m} \frac{S^-}{x_{i0}} \tag{5.17}
$$

Subject to

$$
1 = t + \frac{1}{q_1 + q_2} \left( \sum_{i=1}^{q_1} \frac{S^g}{y_{i0}} + \sum_{i=1}^{q_2} \frac{S^b}{y_{i0}} \right) \tag{5.18}
$$

$$
x_0 = X\lambda + S^- \tag{5.19}
$$

$$
y_0^g = Y^g\lambda - S^g \tag{5.20}
$$

$$
y_0^b = Y^b\lambda + S^b \tag{5.21}
$$

$$
S^- \geq 0, S^g \geq 0, S^b \geq 0, \lambda \geq 0, t \geq 0 \tag{5.22}
$$
Let \((\tau^*, t^*, \lambda^*, S^\tau, S^\lambda, S^t, S^\lambda)\) be the optimal solution of the linear program. Then, the optimal solution of original program (5.2)-(5.5) is

\[
\begin{align*}
\rho^* &= \tau^* / t^*, \\
\lambda^* &= \lambda^* / t^*, \\
S^\tau &= S^\tau / t^*, \\
S^\lambda &= S^\lambda / t^*.
\end{align*}
\] (5.23)

In this study, there are four inputs, viz., capital, labor, water, and energy; one desirable output, i.e., industrial output; and three undesirable outputs, viz., wastewater discharges, waste gas emissions, and soot emissions. Note that raw materials are also important inputs. However, they are not explicitly included in the DEA because in the database, they are merged with capital. Using slack variables, the energy efficiency (EEF), wastewater 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. **EEF** defined as:

\[
EEF = \frac{AE - ExcessE}{AE}
\] (5.24)

measures a firm’s distance from the energy-efficiency frontier (Hu and Wang, 2006; Wei et al. 2009), where \(AE\) is the actual energy input, and \(ExcessE\) is the excess energy input. \(AE-ExcessE\) is the target energy input that represents the best level—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** is thus restricted to the interval \((0, 1]\).

The slack variable of pollutant \(k\) (\(k\) denotes wastewater, waste gas or soot in this study) is the excess emission of pollutant \(k\). Similar to (5.24), \(EnvEF\) is the ratio of the target emission to the actual emission (Chang et al., 2013; Tao and Zhang, 2013). For pollutant \(k\), it reads as follows:

\[
EnvEF_k = \frac{AE_{M_k} - Excess_{EM_k}}{AE_{M_k}}
\] (5.25)
where $AEM_k$ is the actual emission level of pollutant k, and $ExcessEM_k$ is the excess emission level of pollutant k. $AEM_k - ExcessEM_k$ is the target emission of pollutant k and represents the best practical minimum level of pollutant k. $EnvEF_k$ is restricted to the interval $(0, 1]$. Based on (5.25), $WWEF$, $WGEF$, and $STEF$ are derived.

The slack of industrial output represents the shortage in desirable output. The target output level is the sum of actual output plus (minimum) shortage in output ($Shortcut$). $OutEF$ is thus defined as (Gómez-Calvet et al., 2014):

$$OutEF = \frac{AO}{AO + Shortcut}$$

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

### 5.2.2 Structural equation model (SEM)

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

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

$$y = \Lambda_y \eta + \varepsilon$$
$$x = \Lambda_x \xi + \delta$$

where $y$ is a $p \times 1$ vector of endogenous observed variables, $x$ is a $q \times 1$ vector of exogenous observed variables, $\eta$ is an $m \times 1$ vector of latent endogenous variables, and $\xi$ is an $n \times 1$ vector of latent exogenous variables. $\Lambda_y$ and $\Lambda_x$ are $p \times m$ and $q \times n$ matrices of loadings (coefficients) for $\eta$ and $\xi$, respectively. $\varepsilon$ and $\delta$ are $p \times 1$ and $q \times 1$ 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).

Next is the structural model that specifies the relationships among the latent variables. This model reads as follows:

$$\eta = B\eta + \Gamma \xi + \zeta$$

(5.28)

where $B$ is an $m \times n$ matrix where $\beta_{ij}$ represents the relationships among the latent endogenous variables; $\Gamma$ is an $m \times n$ matrix giving the effects of the exogenous latent variables on the endogenous latent variables; and $\zeta$ is 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 both the measurement models and the structural model by taking that variable as identical to its corresponding latent variable (loading equal to 1 and measurement error equal to 0). Furthermore, it is possible to include intercepts both in the measurement models and in the structural model (Jöreskog & 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 $STEF$, which are obtained from equations (5.24) and (5.25). A third endogenous latent variable, $Profit$, is included in the structural model and is taken as identical to the observed $Profit$. It is hypothesized that $Profit$ has positive impacts on either or both $OutEF$ and $EnvEF$, because ceteris paribus, a firm with higher profits has more resources than a firm with lower profits to improve efficiency. 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. Conversely, efficiency improvement requires expenditures on equipment and training, which lowers profits, ceteris paribus. As outlined in the introduction, direct interactions between $EnvEF$ and
OutEF are also hypothesized.

The analyzed data set contains several exogenous variables (controls) that are assumed to impact 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 several of the endogenous variables. For Clratio, which is the vintage of capital, a high value indicates new, high-tech capital, whereas a low value indicates old-fashioned capital (Metcalf, 2008; Wang, 2011; Wu, 2012). Clratio is thus expected to directly affect Profit, EnvEF and OutEF. More specifically, a positive impact on environmental efficiency is likely, because new vintage capital tends to be more environmentally friendly, especially with respect to energy efficiency (Wu, 2012). Liabilities (defined as the total of all financial obligations) and Taxes (defined as taxes and surcharges paid for main operations and composed of business tax, urban construction and maintenance tax, resource use tax, and land appreciation tax) imply additional costs and are thus 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. Size, however, is likely to have positive impacts on all three endogenous variables because of large firms’ ability 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 are assumed to positively affect both Profits and the efficiency variables. Finally, because it accompanies both knowledge accumulation and learning by doing, Age is likely to positively affect both Profit and OutEF. Note that there are also variables that impact the endogenous variables but that are constant for all of the firms in the data set. For example, both norms and legislation impact EnvEF. Such variables are constant because the affected firms belong to the same jurisdiction (Jiangsu). Thus, omission of these variables does not lead to omitted variable bias.

Because of identification problems, estimation of SEMs, in which all equations
contain virtually all controls, is infeasible. However, there is little evidence to exclude, a priori the impacts of the controls on the three endogenous variables. To resolve this problem, we adopt a heuristic approach that involves the estimation of several models that differ in terms of restrictions (i.e., zero constraints) on the coefficients in the $\Gamma$ component of the structural model. The final one of the estimated models is chosen based on theoretical plausibility, the significance of the estimated coefficients and the overall goodness of fit. Note that the final model thus obtained is preliminary, especially with respect to the relationships between the controls and the endogenous variables, as it has not been estimated and tested in previous studies and, thus, is based on the present data set only.

In terms of equations (5.27)-(5.28), the SEM efficiency model outlined above reads as follows:

**Measurement model of the endogenous latent variables:**

$$
\begin{bmatrix}
EEF \\
WWEF \\
WGEF \\
STEF \\
OutEF \\
Profit
\end{bmatrix} =
\begin{bmatrix}
1 & 0 & 0 \\
\lambda_{y1} & 0 & 0 \\
\lambda_{y1} & 0 & 0 \\
\lambda_{y4} & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
\text{EnvEF} \\
\text{OutEF} \\
\text{Profit}
\end{bmatrix} +
\begin{bmatrix}
\varepsilon_1 \\
\varepsilon_2 \\
\varepsilon_3 \\
\varepsilon_4
\end{bmatrix}
$$

(5.29)

**Measurement model of the exogenous variables:**

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

(5.30)

**Structural model:**
Note that to render the model identified, the coefficient of $EEF$ is fixed at 1 in equation (5.29), thus assigning a measurement scale to the unobserved latent variable $EnvEF$. Furthermore, in equation (5.30), the latent variables are equal to their observed indicators. As a result, the error terms are fixed at 0.

\begin{equation}
\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}
\end{equation}

\begin{equation}
\begin{bmatrix}
\gamma_{1,1} & 0 & 0 & 0 & 0 \\
0 & \gamma_{1,2} & \gamma_{2,3} & \gamma_{2,4} & 0 \\
0 & 0 & 0 & 0 & \gamma_{3,5} & \gamma_{3,6}
\end{bmatrix}
+ 
\begin{bmatrix}
\varsigma_1 \\
\varsigma_2 \\
\varsigma_3
\end{bmatrix}
\end{equation}

5.3 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), accounting for approximately 6% of China’s total population. Jiangsu is located in the Yangtze River Delta and has an area of 102,600 square kilometers, which is approximately 1.1% of the entire nation’s area (Long and Ng, 2001; Jiangsu Statistical Yearbook 2012).

Jiangsu is one of China’s most economically developed provinces and has a high economic growth rate. Its gross provincial product (GPP) grew from 25 billion Yuan in 1978 to 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 GPP accounted for nearly 10% of China’s GDP in 2011 (NBS, 2012). Among the 31 Chinese provinces (excluding Taiwan, Hong Kong, and Macau), Jiangsu’s GPP ranked second only to Guangdong province. However, its rapid economic growth has been accompanied by substantial energy consumption.

For years, Jiangsu has been suffering from energy shortages. In 2000, Jiangsu
only produced 20 million tons SCE, but it consumed 86 million tons, resulting in a
deficiency of 66 million tons. In 2011, Jiangsu’s energy consumption of 276 million
tons SCE far 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. Jiangsu 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. Jiangsu also lacks hydro power because
geographically, it is a plain. It is relatively rich in wind power, however. Jiangsu thus
heavily depends on energy imports from energy-rich provinces.

Jiangsu heavily depends on the use of coal (more than 70% in 2011), which has
been the primary cause of environmental degradation. In 2011, SO$_2$ emissions were
1.1 million tons, NO$_x$ emissions were 1.5 million tons, and smoke and dust emissions
were 0.5 million tons. These pollutants have seriously deteriorated Jiangsu’s
environment.

Energy-efficiency improvement has played a major role in reducing Jiangsu’s
energy consumption and emissions. 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, Jiangsu still lags behind developed countries (Hong et al., 2013), thus
indicating that the province has a huge potential to improve its energy efficiency. In
the 11$^{th}$ Five-Year Plan (2006–2010), Jiangsu was assigned a specific target of
improving energy efficiency by 20%. By the end of 2010, it had successfully reduced
its energy consumption per unit of GPP by 20.5% (Duan and Hu, 2014). However, no
targets were set for Jiangsu’s main pollutants.

The data set includes 137 firms classified into 3 manufacturing sectors at the
2-digit level, based on the “Classification and code standard of national economy
industry” released by the National Bureau of Statistics of China (source:
“wearing apparel and accessories manufacturing”, and “leather, fur, feather and
related products and footwear manufacturing”, are grouped into a single group—viz.,
textile—according to the similarities among products. Data are available for 2009 only. Data for capital, labor, and industrial output value are obtained from the Chinese Industrial Enterprises Database, which is not publicly available. Data for water use, energy consumption, wastewater discharges, waste gas emissions, and soot emissions are obtained from Jiangsu’s Environmental Protection Department. Table 5.1 presents the definitions, units of measurement, and descriptive statistics (mean, standard deviation (SD), minimum (Min) and maximum (Max)) of the input and desirable and undesirable output variables analyzed using the GDEA. Note that because of data limitations, the only energy source considered is coal. Thus, the energy-efficiency indicator below is actually a “coal indicator”. This limitation affects the environmental efficiency analysis only marginally because coal is by far the most important energy source in the Jiangsu textile industry.

Table 5.1 Input and output variables of the GDEA

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Unit</th>
<th>Mean</th>
<th>S.D.</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capital</td>
<td>Value of fixed assets</td>
<td>Million Yuan</td>
<td>70.38</td>
<td>361.28</td>
<td>0.63</td>
<td>4170.39</td>
</tr>
<tr>
<td>Labor</td>
<td>Number of employees</td>
<td>Capita</td>
<td>514.25</td>
<td>1314.71</td>
<td>30.00</td>
<td>14300.00</td>
</tr>
<tr>
<td>Energy</td>
<td>Coal consumption</td>
<td>Tons</td>
<td>6775.10</td>
<td>16876.5</td>
<td>5</td>
<td>146515.0</td>
</tr>
<tr>
<td>Water</td>
<td>Water use</td>
<td>Thousand Tons</td>
<td>635.00</td>
<td>900.75</td>
<td>10.00</td>
<td>8724.47</td>
</tr>
<tr>
<td>Output</td>
<td>Industrial output value</td>
<td>Million Yuan</td>
<td>285.23</td>
<td>1389.36</td>
<td>6.70</td>
<td>16005.16</td>
</tr>
<tr>
<td>Wastewater</td>
<td>Volume of wastewater discharges</td>
<td>Thousand Tons</td>
<td>480.78</td>
<td>690.57</td>
<td>0.80</td>
<td>6979.58</td>
</tr>
<tr>
<td>Waste gas</td>
<td>Volume of waste gas emissions</td>
<td>Million Cubic Meters</td>
<td>70.00</td>
<td>169.68</td>
<td>1.20</td>
<td>1465.15</td>
</tr>
<tr>
<td>Soot</td>
<td>Volume of soot emissions</td>
<td>Tons</td>
<td>37.43</td>
<td>64.34</td>
<td>0.75</td>
<td>455.00</td>
</tr>
</tbody>
</table>

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

Data for the controls in the SEM are from the Chinese Industrial Enterprises Database. Table 5.2 presents their definitions, units of measurement, and descriptive statistics.

Table 5.2 The SEM control variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Unit</th>
<th>Mean</th>
<th>S.D.</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
</table>

23 For the purposes of this study, the data were made available to the third co-author.
Empirical results

Table 5.3 presents descriptive statistics on the output of the GDEA (equations (5.17)-(5.23), i.e., the efficiency indices $GEF$, $EEF$, $WWEF$, $WGEF$, $STEF$, and $OutEF$). The table shows that generalized efficiency has the lowest mean among all of the efficiency measures because it is a multi-factor efficiency measure based on the inputs and outputs. This statistic indicates substantial potential either to save inputs or to improve outputs.

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 because they are all 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 5.4-5.6. The Initial Model in
Table 5.4 includes all of the relevant variables in the data set (briefly discussed in section 5.2). However, the variable Age turned out to be highly insignificant in all of the models and was deleted from the analysis. The resulting model is the Final Model.

Table 5.4 presents the overall-goodness-of-fit measures of both the Initial Model (including Age) and the Final Model (without Age): the $\chi^2$/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 $\chi^2$ based test. However, the test is highly sensitive to deviation from normality and is hampered by the small sample size (Jöreskog and Sörbom (2001), Hox and Bechger (1998)). Under these conditions, the fit measures $\chi^2$/df and RMSEA are more appropriate.) From Table 5.4, it follows that the goodness-of-fit statistics of both the Initial and Final Models meet their critical values, although the $\chi^2$/df and the RMSEA of the former are slightly better than those of the latter. Based on these results, the Final Model is now discussed.

**Table 5.4 SEM goodness-of-fit statistics**

<table>
<thead>
<tr>
<th></th>
<th>$\chi^2$/df</th>
<th>RMSEA</th>
<th>GFI</th>
<th>AGFI</th>
<th>CFI</th>
<th>NFI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Model</td>
<td>1.639</td>
<td>0.064</td>
<td>0.94</td>
<td>0.86</td>
<td>0.98</td>
<td>0.95</td>
</tr>
<tr>
<td>Final Model</td>
<td>1.806</td>
<td>0.073</td>
<td>0.93</td>
<td>0.86</td>
<td>0.98</td>
<td>0.96</td>
</tr>
<tr>
<td>Cut-off value</td>
<td>&lt;3</td>
<td>&lt;0.08</td>
<td>&gt;0.90</td>
<td>&gt;0.80</td>
<td>&gt;0.90</td>
<td>&gt;0.90</td>
</tr>
</tbody>
</table>

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

The modification indices of the structural model presented in Table 5.5 give hints about incorrectly fixed or constrained parameters. More precisely, a modification index is the predicted decrease in $\chi^2$ if a single fixed parameter or equality constraint 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 5.5 shows that none of the fixed parameters exceeds the critical value, which supports the parameter configuration (i.e., the fixed (at 0) and free, estimated parameters).
Table 5.5 Matrix of modification indices of the SEM

<table>
<thead>
<tr>
<th></th>
<th>EnvEF</th>
<th>OutEF</th>
<th>Profit</th>
</tr>
</thead>
<tbody>
<tr>
<td>EnvEF</td>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>OutEF</td>
<td>0.04</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Profit</td>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Clratio</td>
<td>---</td>
<td>0.00</td>
<td>0.08</td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Taxes</td>
<td>3.22</td>
<td>---</td>
<td>0.42</td>
</tr>
<tr>
<td>Size</td>
<td>0.58</td>
<td>---</td>
<td>0.68</td>
</tr>
<tr>
<td>Liabilities</td>
<td>2.48</td>
<td>0.15</td>
<td>---</td>
</tr>
<tr>
<td>Sales</td>
<td>0.79</td>
<td>0.15</td>
<td>---</td>
</tr>
</tbody>
</table>

Note: critical value: 7.

Table 5.6 presents the estimated measurement models. Before discussing the results, note that the estimated coefficients are standardized (beta) coefficients. These are directly comparable because a beta coefficient represents the standard deviation change in an endogenous variable caused by a standard deviation change in an explanatory variable (Wooldridge, 2012). Note that standardization also affects the coefficients of the indicators EEF, OutEF, and Profit, which were originally fixed at 1.

Table 5.6 shows that all of the 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). Thus, EnvEF is measured well. Note also that the loadings of the indicators are virtually equal.

Table 5.6 The SEM measurement model

<table>
<thead>
<tr>
<th>Latent variable</th>
<th>Indicator</th>
<th>Coefficient</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>EEF</td>
<td>0.33</td>
<td>0.94</td>
</tr>
<tr>
<td></td>
<td></td>
<td>---</td>
<td></td>
</tr>
<tr>
<td></td>
<td>WWEF</td>
<td>0.31***</td>
<td>0.73</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.05)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>17.46</td>
<td></td>
</tr>
<tr>
<td>EnvEF</td>
<td>WGEF</td>
<td>0.33***</td>
<td>0.97</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.03)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>35.43</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.33***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>STEF</td>
<td>(0.05)</td>
<td>0.82</td>
</tr>
<tr>
<td></td>
<td></td>
<td>21.54</td>
<td></td>
</tr>
<tr>
<td>OutEF</td>
<td>OutEF</td>
<td>0.27</td>
<td>1.00</td>
</tr>
</tbody>
</table>

132
<table>
<thead>
<tr>
<th>Variable</th>
<th>EnvEF</th>
<th>OutEF</th>
<th>Profit</th>
</tr>
</thead>
<tbody>
<tr>
<td>EnvEF</td>
<td>---</td>
<td>0.62***</td>
<td>-0.98***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.10)</td>
<td>(0.06)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>5.18</td>
<td>-2.82</td>
</tr>
<tr>
<td>OutEF</td>
<td>---</td>
<td></td>
<td>-1.47***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.10)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-3.46</td>
</tr>
<tr>
<td>Profit</td>
<td>1.18***</td>
<td>0.30***</td>
<td>---</td>
</tr>
<tr>
<td></td>
<td>(1.81)</td>
<td>(0.52)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3.56</td>
<td>2.56</td>
<td></td>
</tr>
<tr>
<td>Clratio</td>
<td>-0.23*</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td></td>
<td>(0.53)</td>
<td></td>
<td>-1.88</td>
</tr>
<tr>
<td>Taxes</td>
<td>---</td>
<td>-0.26***</td>
<td>---</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.06)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>-3.26</td>
<td></td>
</tr>
<tr>
<td>Size</td>
<td>---</td>
<td>0.48***</td>
<td>---</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.04)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>6.21</td>
<td></td>
</tr>
<tr>
<td>Liabilities</td>
<td>---</td>
<td>---</td>
<td>-1.19***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.03)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-3.56</td>
</tr>
<tr>
<td>Sales</td>
<td>---</td>
<td>---</td>
<td>2.37***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.06)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>4.34</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.69</td>
<td>0.73</td>
<td>0.79</td>
</tr>
</tbody>
</table>

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

Table 5.7 The SEM structural model

Notes: coefficients are completely standardized coefficients; standard errors within brackets; t-values in italics; *: $p<.10$, **: $p<.05$, ***: $p<.01$. 
The structural model is presented in Table 5.7 and Figure 5.1. Table 5.7 shows that all of the coefficients in the structural model are significant at 10%. Moreover, the three R-squared values are quite high. Below, the two efficiency sub-models are first discussed, followed by the profit sub-model.

Profit has a positive impact on EnvEF, indicating that profit induces EnvEF. Clratio, however, negatively and significantly impacts EnvEF. One possible explanation for this result is that the textile industry is still labor-intensive instead of capital- and energy-intensive. A 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 it was highly insignificant. Therefore, it was 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 the reduction of inputs, notably energy inputs. The positive impact of Profit on OutEF implies that a high-profit firm can save on costs, e.g., via the installment of efficient capital. Taxes have a negative 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 Profit, indicating that both types of efficiency improvement absorb resources at the expense of Profit. Liabilities also have a negative impact on Profit. Sales, however, positively impact Profit, indicating that a firm with high turnover tends to have high profits.

Table 5.8 Standardized total effects of the SEM

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

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

Table 5.8 presents the total effects of all of the 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
5.7). 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 either 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 $EnvEF$, whereas $EnvEF$ 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 turn has a positive impact on $EnvEF$ (1.18). The effect of $Tax$ 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 between $EnvEF$ and $Profit$. Thus, its total effect on $EnvEF$ amounts to 0.12. $Sales$ (0.76) have 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 of $OutEF$ 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, $Sales$ have a positive total effect via $Profit$. $Taxes$ (-0.15) and $Liabilities$ (-0.33) have negative total effects on $OutEF$ which also has a negative effect on itself via $Profit$. The negative total effect of $Liabilities$ (-0.33) comes from the indirect effect via $Profit$.

The variables with negative total effects on $Profit$ are $EnvEF$ (-0.51), $OutEF$ (-0.40), $Liabilities$ (-0.32) and $Size$ (-0.19), whereas $Profit$ (-0.73) also has 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 $Profit$ via $OutEF$, although it,
too, has no direct effect. 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 that feedback on Profit.

5.5 Conclusion and policy recommendations

This paper’s primary purpose was to analyze the interaction between environmental efficiency and output efficiency, particularly with respect to whether they reinforce 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. In the first step, efficiency measures for energy (EEF), wastewater (WWEF), waste gas (WGEF), soot (STEF), and output (OutEF) were calculated using GDEA, taking capital, labor, water, and energy as inputs; the industrial output value as the desirable output; and wastewater discharges, waste gas emissions, and soot emissions as undesirable outputs. In the second step of the analysis, the interaction between the two efficiency measures was analyzed using an SEM with latent variables. The input into the SEM was obtained from the GDEA. Environmental efficiency (EnvEF) was measured using the four environmental indicators, and output efficiency (OutEF) was taken as identical to the observed OutEF. Profit was also included in the SEM as an endogenous variable.

The main findings of the analysis are as follows. Environmental efficiency has a negative impact on profit, whereas profit has a positive impact on environmental efficiency. A similar relationship holds for output efficiency and profit: output efficiency reduces profit, whereas profit induces output efficiency. The rationale is that efficiency improvement requires resources, which depress profit. Furthermore, environmental efficiency positively affects output efficiency, but there is no reverse effect. With respect to the control variables, the capital labor ratio, taxes and liabilities negatively and significantly affect environmental efficiency, output efficiency and profit, respectively. Firm size, however, has a positive impact on output efficiency, and sales have a positive impact on profit.
The finding that environmental efficiency induces output efficiency has implications for environmental policy, at least in sectors such as Jiangsu’s textile sector. First, the results indicate that although environmental policy is aimed at improving environmental efficiency, particularly energy efficiency, it both depresses profit and 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 desirable not only from an environmental and energy policy point of view but also from a broader economic perspective because rising production costs have increasingly begun to hamper Chinese exports (Singh and Mahmood, 2014). This is in line with IEA (2014), which shows that investment in energy efficiency may confer several benefits upon firms. Obviously, investment in energy efficiency directly reduces both energy demand and associated costs. Moreover, it may facilitate the achievement of certain objectives, for example, boosting industrial productivity. Further stimulation of environmental and energy efficiency also fits into the national 11th Five-Year Plan (2006–2010) along with its follow up, the 12th Five-Year Plan (2010–2015). It follows that investment in energy efficiency leads to a win-win situation, which may facilitate firms’ adoption of such environmental policies. A possible energy-efficiency stimulating policy is a tax swap of general taxes for an energy tax. As shown in the above analysis, taxes impair a firm’s output efficiency. Conversely, an energy tax is a stimulus to reduce energy use. Therefore, a tax swap is 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, which consists of GDEA and SEM with latent variables, is promising. Moreover, this study relates to China. However, environmental degradation, energy shortage and energy efficiency are also major issues in other developing countries such as India, Pakistan, Bangladesh, Indonesia and several African and Latin American countries. The
analyses applied here could be readily applied in other (developing) countries.
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