Journal of Cleaner Production xxx (2015) 1–10

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

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

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A R T I C L E I N F O

Article history:
Received 28 May 2015
Received in revised form
27 October 2015
Accepted 23 November 2015
Available online xxx

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

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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http://dx.doi.org/10.1016/j.jclepro.2015.11.068
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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.

Please cite this article in press as: Jiang, L., et al., Interaction between output efficiency and environmental efficiency: evidence from the textile industry in Jiangsu Province, China, Journal of Cleaner Production (2015), http://dx.doi.org/10.1016/j.jclepro.2015.11.068