Energy Economics 55 (2016) 42–51

Contents lists available at ScienceDirect

Energy Economics

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

Energy efficiency in Swedish industry A firm-level data envelopment analysis

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ARTICLE INFO

Article history:
Received 2 February 2015
Received in revised form 30 December 2015
Accepted 31 December 2015
Available online 3 February 2016

JEL classification:
D22
D24
L60
Q41

Keywords:
Energy efficiency
EU ETS
Data envelopment analysis
Double bootstrap

ABSTRACT

This paper assesses energy efficiency in Swedish industry. Using unique firm-level panel data covering the years 2001–2008, the efficiency estimates are obtained for firms in 14 industrial sectors by using data envelopment analysis (DEA). The analysis accounts for multi-output technologies where undesirable outputs are produced alongside with the desirable output. The results show that there was potential to improve energy efficiency in all the sectors and relatively large energy inefficiencies existed in small energy-use industries in the sample period. Also, we assess how the EU ETS, the carbon dioxide (CO_2) tax and the energy tax affect energy efficiency by conducting a second-stage regression analysis. To obtain consistent estimates for the regression model, we apply a modified, input-oriented version of the double bootstrap procedure of Simar and Wilson (2007). The results of the regression analysis reveal that the EU ETS and the CO_2 tax did not have significant influences on energy efficiency in the sample period. However, the energy tax had a positive relation with the energy efficiency.

1. Introduction

A key objective of the EU's energy and climate targets has been to increase energy efficiency. By 2020, energy efficiency should be increased by 20% from the 1990 level (European Commission, 2010).[1] Further, the EU decided on October 23, 2014, to raise its energy efficiency by at least 27% by 2030. Achieving the goal of increased energy efficiency has multiple purposes. First of all, improving energy efficiency will increase energy security and improve industrial competitiveness. Also, it can reduce greenhouse gas emissions from burning less fossil fuels and contribute to climate change mitigation. In addition to meeting the targets decided in the EU, Sweden has even more ambitious national goals in order to establish a sustainable and competitive low-carbon economy. Swedish energy and climate targets for 2020 are: 20% more efficient energy use compared to the 2008 level (instead of the 1990 level); 40% reduction in greenhouse gases compared to the 1990 level; and at least 50% share of renewable energy in the final energy consumption (Swedish Energy Agency, 2012).

The Swedish industry contributes about 15% of GDP and is the key engine of the country's economic growth (Nauclér et al., 2012). The industry accounts for about 38% of Sweden's final energy consumption. Although the energy use by the industry consists primarily of biofuels and electricity, fossil fuels still accounted for about 22% in 2011, and are responsible for 80% of the greenhouse gas emissions in Sweden (Swedish Energy Agency, 2013). Since the important role the industry has in the economy and environment, it is therefore of particular importance to assess potential energy efficiency improvements in the industry.

The main objective of this study is to assess energy efficiency in Swedish industry. We measure energy inefficiencies that exist in the industry and thus discover the potential of reducing them. Variation in energy efficiency across firms is likely related to differences in characteristics of firm, e.g., firm size and quality of labor. In addition, the variation is still likely to relate to various policy measures, on which we will focus in the present paper. Several policy measures have been taken by Sweden to ensure to achieve the energy and climate targets. The main measures are economic instruments, including energy tax and carbon dioxide (CO_2) tax, together with the EU emissions trading system (EU ETS). A second objective of this study is thus to investigate in which direction and to what degree, these economic instruments affect energy efficiency. We try to answer this question: Have energy and CO_2 taxes as well as the EU ETS created (significant) incentives for firms to efficiently use energy?

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[1] The EU energy and climate targets for 2020 are a reduction in greenhouse gas emission by 20% from 1990 level; a share of 20% renewable energy in final energy consumption; and an increase in energy efficiency by 20% from 1990 level.

http://dx.doi.org/10.1016/j.eneco.2015.12.023
0140-9883/

We obtain the estimates of energy efficiency of firms in 14 Swedish industrial sectors. Data envelopment analysis (DEA) is used to measure technical energy efficiency, and the DEA model is based on a joint production framework, which means that undesirable outputs, e.g., sulfur dioxide (SO_2) and nitrogen oxide (NOx), are simultaneously generated when producing the desirable output. Essentially, we consider the maximum possible proportional energy input reduction that still enables to produce the observed amount of outputs, without requiring any additional amount of other inputs. Our results reveal that there was potential to improve the energy efficiency in all 14 industrial sectors, and that there existed relatively large inefficiencies in firms from the small energy-use industries. Further, in attempts to examine the energy efficiency effect of economic instruments, we conduct a second-stage regression analysis and regress the DEA efficiency estimates on a set of explanatory variables, including economic instruments. Since there exists serial correlation among the DEA efficiency estimates, we get consistent estimates of the regression model by employing a modified, input-oriented double bootstrap technique suggested by Simar and Wilson (2007).[2] The regression analysis reveals that the EU ETS and CO_2 tax did not have significant influences on energy efficiency in the sample period. However, the energy tax had a positive relation with the energy efficiency.

Our empirical application uses a firm-level panel data to assess energy efficiency. The use of firm-level data makes it possible to have a deeper understanding of how economic instruments impact industrial firms' energy performance, and thus enables us to examine whether these economic instruments have created incentives for industrial firms to improve energy efficiency. In this respect, to the best of our knowledge this paper is the first study to carry out such policy analysis based on the DEA approach.

The rest of the paper is organized as follows. Section 2 provides a brief review of the literature. Section 3 describes the background of Swedish energy and CO_2 taxes, as well as the EU ETS. Section 4 describes the joint production DEA model and the double bootstrap procedure which is used to estimate the regression model. Section 5 describes the data set and specifications of empirical models. The results are presented in Section 6. Section 7 concludes.

2. A brief review of the literature

Energy intensity is measured by the ratio of the quantity of energy required to output. The inverse of energy intensity is traditionally used in the literature as a measure of energy efficiency — a lower energy intensity implies a higher energy efficiency (see, e.g., Mukherjee, 2008a). The inverse of energy intensity is considered as a single-factor efficiency measure, because no output would be produced by using a single energy input, without any other inputs (see, e.g., Mukherjee, 2008b). Therefore, it is not an appropriate measure in the context of production with multiple inputs and outputs. In a broad sense, efficiency is defined as the ratio of the optimal input bundle to the actual input bundle, or as the ratio of the actual output to the optimal output. This definition of efficiency was first introduced by Debreau (1951) and Koopmans (1951), and has been widely used in the productive efficiency and productivity literature since the seminal paper of Farrell (1957). In the present paper, the energy efficiency measure is grounded on the definition of technical efficiency defined by Farrell (1957), which we will present in Section 4.

Two approaches are widely used to estimate production frontier and energy efficiency in the literature. One is stochastic frontier analysis (SFA) which uses econometric models to estimate technological frontier and calculate efficiency. Examples of energy efficiency studies using SFA are, inter alia, Feijoo et al. (2002); Boyd (2008); Buck and Young (2007); Filippini and Hunt (2011, 2012); Zhou et al. (2012); Lin and Yang (2013); Lin and Wang (2014); Lin and Long (2015). The SFA method requires specifying a functional form for the technological frontier and distributional assumptions are necessary on the inefficiency. This method enables to distinguish random noises from efficiency. While the distributional assumptions may sometimes cause misspecification issues in empirical analysis, Zhou et al. (2012) show that efficiency estimate results are quite robust to the distributional choices, where the SFA approach is used to estimate the economy-wide energy efficiency for a sample of OECD countries, and the truncated normal and half normal distributions are examined.

DEA, introduced by Charnes et al. (1978), is a nonparametric approach that estimates efficiency by solving mathematical programming models. The DEA approach does not require specifying a functional form for the technological frontier and thus can avoid the misspecification problem which the SFA approach faces. In contrast to SFA, the DEA model does not need any distributional assumptions about the inefficiency. In turn, since no distributional assumptions are imposed, the DEA method is unable to separate random noises from efficiency.

A few DEA studies on energy efficiency analysis can be found in the literature. Ramanathan (2000) measured energy efficiency of different transport modes in the Indian transport sector. Hu and Wang (2006) used a total factor index to examine regional level energy efficiency in China. Azadeh et al. (2007) measured total energy efficiency in four energy-intensive sectors in 10 OECD countries by incorporating structural factors. Mukherjee (2008b) estimated energy efficiency in US manufacturing by using four policy-driven models. Shi et al. (2010) evaluated regional industrial energy efficiency in China using a model with fixed non-energy inputs. Bloomberg et al. (2012) assessed the potential electricity efficiency improvement in Swedish pulp and paper mills, and compared the efficiency estimates with the ones reported by Swedish energy efficiency program (PFE) to assess the program's performance. Wang et al. (2013) estimate energy efficiency and productivity in China, using a non-radial directional distance function. None of the above studies carried out the analysis by using a firm-level panel data.

When undesirable outputs, e.g., SO_2 and NO_x, are generated together with producing desirable outputs, and when the undesirable outputs cannot be disposed of at no cost, it is necessary to include the undesirable outputs when measuring productive efficiency or productivity (Färe et al., 2012). Recently, the environmental DEA technology, which is based on joint production technology and models both desirable and undesirable, has generated widespread applications.[3] Examples, among others, are Färe et al. (1989), Färe et al. (1996), Färe et al. (2004), Tyteca (1996), Seiford and Zhu (2002), Zaim (2004), and Zhou et al. (2008). Zhou and Ang (2008) used a joint production DEA model, which includes as inputs a vector of energy input, to first estimate potential energy savings and then calculate energy efficiency. Since the model allows substitution between various energy inputs, they claim it flexible in a way that energy inputs can be reduced in different proportions. However, since substitution is permitted between different types of energy input, the energy efficiency measure is not pure technical in that it has captured in part allocative efficiency.[4]

[2] Their suggested bootstrap procedure is output-oriented.

[3] The joint production framework with the weak disposability assumption has been criticized by Coelli et al. (2007), Førsund (2009) and Murty et al. (2012). They point out that the material balance principle, which says "what flows in must come out", is violated when the weak disposability of good and bad outputs is imposed. There are exceptions to the problem. One is that, when the good outputs contain zero bad materials, e.g., when electricity is generated by using coal, the good output electricity contains zero bad materials, e.g., sulfur, the material balance principle can be met. The second situation in which the material balance condition still satisfies is that abatements are made on bad outputs (see Coelli et al., 2007; Førsund, 2009; Murty et al., 2012; and Rødseth, 2011). In our empirical application, the good output does not contain any sulfur and nitrogen, and the two bad outputs SO_2 and NOx are measured after abatements. Thus, our empirical model is in accordance with the material balance principle.

[4] Substitution between various types of energy input is intended to reduce cost by substituting the energy with higher price for the one with lower price.