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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 (Journal of Econometrics 136(1):31-64, 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.

JEL-classification: D22; D24; L60; Q41

Key words: energy efficiency, EU ETS, data envelopment analysis, double bootstrap

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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, quality of labor, etc. 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?

[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.

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 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 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

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

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. For instance, Filippini and Hunt (2011, 2012) used the SFA method to estimate energy efficiency in OECD countries and United States, respectively. 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. However, the restrictive distributional assumptions may cause misspecification issues in empirical analysis.

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 U.S. 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. None of the above studies carried out the analysis by using a firm-level panel data.

When undesirable outputs, e.g., SO_2, 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]

In explaining variation in efficiency, a second-stage regression analysis is typically used to examine the effect of environmental factors on the estimated efficiency. Chilingerian (1995), Ruggiero and Vitaliano (1999), and Mukherjee (2008a), among others, carried out the second-stage regression analysis. According to Simar and Wilson (2007), the coefficient estimates obtained by the above studies may not be consistent, since these studies used OLS and/or Tobit regression and have not taken into account the serial correlation of the efficiency estimates. Instead, Simar and Wilson (2007) propose a double bootstrap procedure which can produce consistent estimates of the regression coefficients and provide valid confidence intervals for the estimates. In the present paper, the double bootstrap will be adapted and applied to our regression analysis.

The present study departs from the above empirical energy efficiency studies from some perspectives. First, we use unique firm-level panel data, which covers 14 industrial sectors, to carry out the analysis. Second, to the best of our knowledge, this is the first paper in the DEA framework that examines the economic instruments effect on energy efficiency, and the EU ETS effect in particular. Third, our coefficient estimates in the regression model are consistent and valid for inference, since Simar and Wilson's (2007) double bootstrap procedure is employed for the estimation of the regression equation.

[3] The joint production framework with the weak disposability assumption has been criticized by Coelli et al. (2007), Føsund (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, sulphur, 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; Føsund, 2009; Murty et al., 2012; and Rødseth, 2011). In our empirical application, the good output does not contain any sulphur 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.

3. Policy background: Swedish energy tax, CO_2 tax, and the EU ETS

A collection of policy measures are implemented in Sweden in an effort to achieve its energy and climate targets. The main measures are economic instruments, including energy tax, CO_2 tax and the EU ETS. In this section we provide a brief description of these measures. For a detailed description of them, see Lundgren et al. (2014).

3.1. The Swedish energy tax

Energy has been taxed in Sweden since the 1920s. In 1929 a tax on petrol and motor alcohol was introduced, followed by in 1951 a tax on electricity and in 1957 a general energy tax on fossil fuels. In 1991 the general energy tax was partly replaced by a CO_2 tax. Remarkably, in 1993 an energy tax reform was implemented that raised the energy tax substantially. Due to the high tax rate, the manufacturing industry was exempted from paying the general energy tax. However, in 2004 the tax exemption on electricity was removed. Instead, energy-intensive firms in the industry were required to pay 0.005 SEK per kWh tax on electricity in line with the EU's Energy Tax Directive. These firms still have the opportunity of tax exemption on electricity consumption, if action is taken by them to improve their energy efficiency (Council Directive No. 2003/96/EC). The energy efficiency improvement program (PFE) was introduced in 2005 and it is voluntary for the firms. The PFE gives electricity tax exemption to the firms who participate in the program and are proven to have improved their energy efficiency in a five-year period (Swedish Energy Agency, 2012).

3.2. The Swedish CO_2 tax

The CO_2 tax was introduced in 1991.[5] It partly replaced the already existing energy tax and was levied according to the content of CO_2 in fuels, at SEK 0.25 per kg CO_2 emitted. The 1993 energy tax reform raised the CO_2 tax considerably as well. To relieve some tax burden on the industry, the 1993 energy tax reform also introduced a regulation that requires industrial firms to pay only 25% of the statutory CO_2 tax rate. In 1997 the industry was required to pay 50% of the statutory tax rate (Statistics Sweden, 2000). The tax rate was increased from SEK 0.37 in 2000 to SEK 0.91 in 2004, and SEK 1.01 in 2008 per kg emitted.

There are also, during the time span studied, some additional exemption rules for certain process related emissions (e.g. steel production) and rules (a cap) for how much a firm has to pay in relation to its sales value. These exemption rules make the effective tax in different sectors and across firms vary, which is convenient in our empirical application.

[5] Sweden is one of the first countries to introduce a CO_2 tax (Marchal et al., 2012).

3.3. The EU ETS

The EU ETS, introduced in 2005, is viewed by the EU as an important way to cost-effectively reduce its industrial greenhouse gas emissions, and covers now about 45% of the emissions (European Commission, 2013). The EU ETS works according to a 'cap and trade' principle. A cap, or limit, was placed on overall CO_2 emission allowances at Member State levels according to national allocation plans. Within the cap, firms can buy and sell emission allowances; one emission allowance is equivalent to one ton of carbon dioxide. By reducing the cap each year, total emissions decline, e.g., to attain a 43% reduction in CO_2 emissions in EU by 2030 from the 1990 level, the cap will need to be lowered by 2.2% per year from 2021 (European Commission, 2014). In the first trading period (2005-2007) the system covered CO_2 emissions from power plants and energy-intensive industries, and the allowances were distributed by free allocation. In the second trading period (2008-2012) the total allowances were reduced by 6.5 percent compared to the 2005 level. In the third trading period (2013-2020), the system is significantly changed. A single cap on emissions is decided at the EU level. Auctioning will progressively replace free allocation, and is mainly used for allocating emission allowances. In addition, the system covers more sectors and additional greenhouse gases.

Our study focuses on the Swedish industry and covers the first trading period and the first year of the second trading period of the EU ETS (2005-2008). The CO_2 tax for Swedish industrial firms included in the EU ETS was gradually phased out from 2008 to the end of 2010. In the first trading period (2005-2007), however, the CO_2 tax was still functional.

4 Methods

4.1. Energy efficiency measurement: a joint production technology

Energy efficiency is defined in this paper as the ratio of optimal to actual energy input bundles, holding outputs and non-energy inputs fixed. Since energy reduction is required to be proportional for all energy inputs, it is therefore an input-oriented technical efficiency measure.

Consider a production process that uses a vector of N non-energy inputs $x = (x_1, \ldots, x_N)$ and a vector of L energy inputs $e = (e_1, \ldots, e_L)$ to produce a vector of M desirable outputs $y = (y_1, \ldots, y_M)$, and jointly generate a vector of J undesirable outputs $u = (u_1, \ldots, u_J)$. The technology can be defined as:

$$T = \{(x, e, y, u) : (x, e) \text{ can produce } (y, u)\},$$

which is assumed to be closed and bounded, implying that a finite amount of inputs can only produce a finite amount of outputs. We assume that inputs are strongly disposable, and so are desirable outputs.[6] To model the concept that desirable and undesirable outputs are jointly produced, and to model the idea of costly disposal of undesirable outputs, we further impose two properties on the technology (Färe et al., 1989):

1) Null-joint outputs: $if \ \left(x,e,y,u\right)\in T$ and $u=0,$ then $y=0;$

2) Weak disposability of outputs: $if \ \left(x,e,y,u\right)\in T$ and $\theta\in\left[0,1\right],$ then $\left(x,e,\theta y,\theta u\right)\in T.$

The null-joint says that, if some amount of the desirable outputs are produced, then some undesirable outputs must also be generated; the weak disposability says that, if undesirable outputs are to be reduced by some proportion, then the good outputs must also be reduced by that proportion, while holding the inputs fixed (Färe and Grosskopf, 2004).

To apply the joint production technology T to the empirical application, we can represent it by using DEA. Assume that there are $i=1,\ldots,K$ observations of input and outputs, each of which is associated with a firm. The joint production technology which allows for variable returns to scale (VRS) can be represented by: [7]

[6] The strong disposability of inputs says that increases in any or all inputs will not decrease outputs. The strong disposability of desirable outputs says that reductions in any desirable outputs are feasible, holding the inputs and undesirable outputs fixed (Färe and Grosskopf, 2004).

[7] The technology allowing for constant returns to scale (CRS) can be formulated by excluding the scaling factor δ and constraint $\sum_{i=1}^{K} z_i = 1$. In our empirical application, we also obtained the estimates of energy efficiency by assuming CRS. Comparing the estimates with the ones obtained by assuming VRS, we find that scale inefficiency exists and that the technology exhibited VRS. Thus, we choose to use model (1) to measure energy efficiency.

$$
\begin{aligned}
T = \{\ (x, e, y, u):& \\
&\sum_{i=1}^{K} z_i y_{im} \geq \delta y_m,\ m = 1, \ldots, M \\
&\sum_{i=1}^{K} z_i u_{ij} = \delta u_j,\ \ j = 1, \ldots, J \\
&\sum_{i=1}^{K} z_i y_{in} \leq x_n,\ n = 1, \ldots, N \\
&\sum_{i=1}^{K} z_i e_{il} \leq e_l,\ \ l = 1, \ldots, L \\
&\sum_{i=1}^{K} z_i = 1,\ z_i \geq 0,\ \sigma \geq 1,\ i = 1, \ldots, K\ \},
\end{aligned}
$$

where $z_i,\ i = 1, \ldots, K$, are intensity variables, which can be understood as the extent to which firm i will contribute to constructing the production frontier. The VRS is imposed by constraint $\sum_{i=1}^{K} z_i = 1$. To make the model satisfying the property of weak disposability of outputs, a scaling factor $\delta \geq 1$ is introduced to the right-hand side of both desirable and undesirable output constraints, ensuring that desirable outputs will be reduced in a same proportion as the one in which undesirable outputs are contracted (Färe and Grosskopf, 2004).

Then, the DEA model for measuring the technical energy efficiency of firm k , $k = 1, \ldots, K$, can be written as:

$$
\begin{aligned}
\alpha_k = \max_{\alpha, z_i, \delta}&\ \alpha \qquad\qquad (1) \\
&\sum_{i=1}^{K} z_i y_{im} \geq \delta y_{km},\ m = 1, \ldots, M \\
&\sum_{i=1}^{K} z_i u_{ij} = \delta u_{kj},\ \ \ j = 1, \ldots, J \\
&\sum_{i=1}^{K} z_i y_{in} \leq x_{kn},\ \ \ n = 1, \ldots, N \\
&\sum_{i=1}^{K} z_i e_{il} \leq \alpha e_{kl},\ \ l = 1, \ldots, L \\
&\sum_{i=1}^{K} z_i = 1,\ z_i \geq 0,\ \delta \geq 1,\ i = 1, \ldots, K,
\end{aligned}
$$

where, since the energy reduction is only allowed in proportion α for all L types of energy input, the optimal value of α, denoted by α_k, is a measure of technical energy efficiency, and $\alpha_k \in (0,1]$.[8] An efficient firm has $\alpha_k = 1$, while an inefficient firm will have $\alpha_k < 1$. Essentially, model (1) finds the largest possible proportional reduction in all energy inputs that still enables to produce the observed amount of desirable and undesirable outputs, while no additional amount of any non-energy inputs are needed.

By using energy efficiency estimate, we can calculate the amount of potential CO_2 emission reduction for firm k, denoted by Q_k^*, when the inefficiency is removed, as follows:

$$Q_k^* = (1-\alpha_k)\times Q_k, \tag{2}$$

where Q_k is the amount of CO_2 emission observed for firm k.

4.2. Second-stage regression analysis

In this paper we also intend to provide new insights into the way in which policy measures affects energy efficiency. This is achieved by regressing the DEA efficiency estimates on a set of policy measure variables and control variables. Suppressing subscript t denoting year, the regression equation can be written as:

$$\alpha_k = f_k\beta + \varepsilon_k, \tag{3}$$

Where α_k is energy efficiency estimate obtained by using model (1), f_k is the vector of explanatory variables, e.g., energy tax, β are parameters to be estimated, and ε_k is the disturbance term.

Ordinary least squares (OLS) can be used to estimate (3). Still, an alternative method is to treat α_k as being censored (for values above 1) and use Tobit model to estimate (3).[9] However, Simar and Wilson (2007) pointed out that there exist serious problems associated with estimating (3) and drawing inference

[8] Allowing α to be energy input specific requires specifying a weighting for each type of energy input, as presented in Zhou and Ang (2008). As such, however, the energy efficiency measure does not measure a pure technical energy efficiency.

[9] The estimated efficiency score α_k by using model (1) is right censored at 1 as it is equal to the actual (latent) score whenever the actual score is <1. When the actual score is ≥ 1, however, the estimated score is always 1 due to the censoring (Mukherjee, 2008a, footnote 17). This is potentially a problem econometrically.

about β. The value of dependent variable α_k is not observed, but estimated by solving model (1). When α_k is used as dependent variable in regression analysis, two issues concerning it must be considered. One problem is that α_k are serially correlated.[10] Another problem is that α_k is biased, though consistent.[11] Simar and Wilson (2007) states that it is unable to provide consistent and valid inference for the coefficient estimates which are obtained by using either OLS or Tobit. To overcome the difficulty, Simar and Wilson (2007) suggests a double bootstrap procedure, which can yield consistent and valid inference for β in (3) by using the method of maximum likelihood estimation. Briefly, the first bootstrap is used to produce a bias-corrected $\hat{\alpha}_k$ for α_k; Replacing α_k with $\hat{\alpha}_k$ in (3), the second bootstrap is used to provide valid inference about β.

The bootstrap algorithm (II) of Simar and Wilson (2007) is designed for output-oriented efficiency measure and cannot be directly applied to our regression analysis, since our efficiency measure is input-oriented. We need to adapt the original algorithm. Since the present paper is the first study on energy efficiency to use the double bootstrap, we describe in detail the adapted algorithm. Below we will use the DEA model (1) and regression equation (3) as an illustrative example to describe the algorithm.

Double bootstrap algorithm II (input-oriented):

[S1] Use model (1) and the original data, calculate α_k, $k = 1, \ldots K$.

[S2] Use the maximum likelihood estimation method to get an estimate $\hat{\beta}$ of β and an estimate $\hat{\sigma}_\varepsilon$ of σ_ε in the truncated regression of α_k on f_k in (3) using $H_0 < K$ observations, which have $\alpha_k < 1$.[12]

[S3] Repeat the following four steps ([S3.1]-[S3.4]) L_1 times to obtain K sets of bootstrap estimates $\mathcal{B}_k = \left\{\alpha^*_{kb}\right\}_{b=1}^{L_1}$:

[10] The correlation occurs in finite samples in that a change in the efficient observations (which are on the estimated frontier) will lead to changes in efficiencies estimated for the inefficient observations (Simar and Wilson, 2007: 33).

[11] Simar and Wilson (2007) proved that α_k is a consistent estimator of the true efficiency, with convergence rate of $K^{-2/(P+1)}$, where P is the total number of inputs and outputs. The rate of convergence is low, and slows as P increases. As a result, in finite samples, α_k is biased.

[12] The double bootstrap of Simar and Wilson (2007) is grounded on the assumption that the explanatory variables are allowed to affect only efficiency scores, not the frontier. If the variable is important for production frontier, it should be included in the DEA model (Benito et al., 2014). Therefore, only inefficient observations, which have $\alpha_k < 1$, are used in the regression.

[S3.1] Draw ε_k for each $k = 1,\ldots,K$ from the $N(0,\hat{\sigma}_{\omega})$ distribution with left truncation at $0 - f_k\hat{\beta}$ and right truncation at $1 - f_k\hat{\beta}$.[13]

[S3.2] Calculate $\overline{\alpha}_k^* = f_k\hat{\beta} + \varepsilon_k$ for each $k = 1,\ldots,K$.

[S3.3] Let $y_k^* = y_k$, $u_k^* = u_k$, $x_k^* = x_k$ and $e_k^* = e_k \times \overline{\alpha}_k^* / \alpha_k$, for each $k = 1,\ldots K$.[14]

[S3.4] Again, use model (1) to calculate α_k^*, by replacing y_k, u_k, x_k, and e_k with y_k^*, u_k^*, x_k^*, and e_k^* respectively.

[S4] For each $k = 1,\ldots,K$, using the bootstrap estimates in $\mathcal{B}_k$ and the original estimate α_k, compute the bias-corrected efficiency estimate $\hat{\alpha}_k = \alpha_k^* + Bias(\alpha_k^*)$, where $Bias(\alpha_k^*) = E(\alpha_k^*) - \alpha_k$.

[S5] Use the maximum likelihood estimation method to regress the truncated regression of $\hat{\alpha}_k$ on f_k, and get estimates $\hat{\hat{\beta}}$ and $\hat{\hat{\sigma}}_{\varepsilon}$. In the regression $H_1 < K$ observations which have $\hat{\alpha}_k < 1$ should be used.

[S6] Repeat the following three steps ([S6.1]-[S6.3]) L_2 times to obtain a set of bootstrap estimates

$$\mathcal{C} = \left\{ (\hat{\hat{\beta}}^*,\ \hat{\hat{\sigma}}_{\varepsilon}^*)_c \right\}_{c=1}^{L_2}$$

[S6.1] For each $k = 1,\ldots,K$, draw ε_k from the $N(0,\hat{\hat{\sigma}}_{\varepsilon})$ distribution with left truncation at $(0 - f_k\hat{\hat{\beta}})$ and right truncation at $(1 - f_k\hat{\hat{\beta}})$.

[S6.2] For each $k = 1,\ldots,K$, compute $\overline{\alpha}_k^{**} = f_k\hat{\hat{\beta}} + \varepsilon_k$.

[13] Simar and Wilson (2007) consider the output-oriented efficiency measure. Since the measure is no less than 1, only the left truncation of the efficiency distribution is assumed. In the present paper, the input-oriented energy efficiency measure $\alpha_k \in (0,1]$, thus both left and right truncations are assumed.

[14] The original algorithm presented in Simar and Wilson (2007) corrects the outputs since the efficiency measured is output-oriented. In the present paper, we correct the inputs because our efficiency measure is input-oriented and output is assumed fixed. The non-energy inputs are also not corrected since they are assumed fixed. The correct factor for energy inputs is obtained by dividing the new efficiency $\overline{\alpha}_k^*$ obtained in step [S3.2] by the original efficiency estimates α_k obtained in step [S1].

[S6.3] Use the maximum likelihood estimation method to get estimates $\hat{\hat{\beta}}$ and $\hat{\hat{\sigma}}_{\varepsilon}$ in the truncated regression of $\bar{\alpha}_k^{**}$ on f_k using $H_2 < K$ observations which have $\bar{\alpha}_k^{**} < 1$

[S7] Use the bootstrap estimates in $\mathcal{C}$ and the original estimates $\hat{\hat{\beta}}$ and $\hat{\hat{\sigma}}_{\varepsilon}$ to construct confidence intervals for $\hat{\hat{\beta}}^*$ and $\hat{\hat{\sigma}}_{\varepsilon}{}^*$.[15]

5. Data and empirical specifications

5.1. Data

The empirical application examines energy efficiency in Swedish industry, followed by analyzing how the policy measures taken by Sweden affect energy efficiency. We use a firm-level panel data to obtain the DEA efficiency estimates and then conduct a second-stage regression analysis. The data on the variables used in both the DEA and the regression analysis are collected and offered by Statistics Sweden (Swedish: Statistiska centralbyrån, SCB). The panel data is unbalanced, has 11 510 observations, and covers the years 2001 to 2008. In total, there are 3 066 firms distributed in 14 industrial sectors: pulp and paper, basic iron and steel, chemicals, stone and mineral, mining, food, wood products, motor vehicles, machinery, rubber and plastic, electro, textiles, fabricated metal products, and printing. The descriptive statistics of the variables are summarized in Table 1 for observations between 2001 and 2008, and Table A for observations in 2001 and 2008. Note that all monetary values in this paper are in 2008 SEK. Below we present Table 1, while Table A is presented in the Appendix.

The number of firms which are included in the EU ETS is 111, of which 42 firms come from the pulp and paper industry, 8 firms from the basic iron and steel industry, 16 firms from the chemicals industry, and 17 firms from the wood products industry. During the period, firms in the pulp and paper, chemicals, and motor vehicles industries, on average, paid higher CO_2 tax; but all firms in the electro, textiles and printing industries did not pay it at all. Firms in the chemicals, motor vehicles, and machinery industries, on average, paid on higher energy tax; but all firms in the fabricated metal products and printing industries did not pay it at all. In addition, all firms in the fabricated and metal products, and printing industries did not have R&D investment on environmental protection.

[15] For a detailed description of how to construct and calculate confidence intervals, see Simar and Wilson (2007: 43).

Table 1. Summary statistics of variables by sector. Firm level, 2001-2008 (standard deviation in the parentheses)

Sector	Sales	SO_2	NOx	Capital	Labor	Fossil fuel	Non fossil	CO_2 tax	Energy tax	R&D	obs.	firms	ETS firms
	(MSEK)	(ton)	(ton)	(MSEK)		(GWh)	(GWh)	(SEK/kg)	(SEK/kWh)	(MSEK)			
PAP	1051	30	50	833	396	75	397	0.246	0.002	0.217	640	114	42
	(1675)	(56)	(95)	(1434)	(552)	(131)	(832)	(0.530)	(0.003)	(0.798)			
BIS	1148	302	177	687	504	386	183	0.078	0.001	0.214	253	53	8
	(2201)	(1467)	(822)	(1468)	(810)	(1653)	(363)	(0.102)	(0.001)	(1.047)			
CHM	662	5	6	540	283	27	52	0.444	0.007	0.120	749	161	16
	(2626)	(21)	(18)	(2431)	(995)	(81)	(170)	(1.259)	(0.028)	(1.309)			
MIN	922	56	234	66	441	157	234	0.085	0.002	0.763	102	34	2
	(1995)	(140)	(709)	(3222)	(892)	(376)	(531)	(0.107)	(0.002)	(4.471)			
WOD	224	2	6	71	93	1	31	0	0.002	0.002	1267	371	12
	(483)	(4)	(13)	(179)	(177)	(6)	(73)	(0)	(0.004)	(0.019)			
STN	69	6	24	88	151	41	13	0.106	0.001	0.030	646	165	17
	(279)	(31)	(156)	(154)	(222)	(183)	(44)	(0.110)	(0.001)	(0.168)			
FOD	437	1	2	148	197	9	11	0.124	0.003	0.005	1551	356	6
	(1114)	(4)	(5)	(435)	(478)	(23)	(30)	(0.186)	(0.005)	(0.044)			
MOT	2041	2	2	632	649	8	22	0.390	0.006	0.056	726	183	4
	(9165)	(17)	(9)	(2715)	(2319)	(28)	(78)	(0.518)	(0.007)	(0.481)			
MAC	298	0.107	0.259	69	177	1	5	0.074	0.016	0.036	2020	553	0
	(963)	(0.355)	(0.647)	(187)	(415)	(3)	(16)	(0.303)	(0.062)	(0.700)			
RUB	125	0.094	0.445	57	95	2	6	0.161	0.002	0.005	798	211	2
	(195)	(0.230)	(1.292)	(97)	(122)	(7)	(12)	(0.349)	(0.002)	(0.042)			
ELE	1012	0.156	0.308	67	352	5	6	0	0.006	0.025	628	186	2
	(5429)	(0.821)	(0.960)	(163)	(1360)	(2)	(20)	(0)	(0.011)	(0.211)			
MET	33	0.046	0.127	16	39	1	2	0.022	0	0	1301	426	0
	(71)	(0.236)	(0.610)	(27)	(98)	(3)	(5)	(0.059)	(0)	(0)			
TEX	68	0.542	0.737	34	68	3	2	0	0.001	0.011	401	107	0
	(102)	(1.612)	(1.461)	(84)	(102)	(7)	(4)	(0)	(0.001)	(0.096)			
PRN	63	0.021	0.221	37	69	1	3	0	0	0	428	146	0
	(136)	(0.041)	(0.553)	(65)	(115)	(2)	(5)	(0)	(0)	(0)			

Note: PAP = pulp and paper; BIS = basic iron and steel; CHM = chemicals; STN = stone and minerals; MIN = mining; FOD = food; WOD = wood products; MOT = motor vehicles; MAC = machinery; RUB = rubber and plastic; ELE = electro; TEX = textiles; MET = fabricated metal products; and PRN = printing.

Table 2 provides the energy consumption by sector in 2001 and in 2008. Percentage figure in column 2 is the proportion of energy use by the sector in the total energy use. Columns 3 and 4 report separately the share of fossil fuel and the share of non-fossil fuel in the corresponding industry. At the entire industry level, the non-fossil fuel use increased from 65.5% in 2001 to 68.2% in 2008. A large increase occurred in the chemicals industry, where the non-fossil fuel increased from 61.4% to 71.1%.

Looking at the energy use by sector (column 2), we see that the pulp and paper industry, the iron and steel industry, and the chemicals industry were the three largest energy users, together accounting for 70.9% and 70.5% of the total energy use in 2001 and in 2008, respectively. The pulp and paper industry, the largest user, accounted for 41.9% and 44% of the total energy use, respectively, in 2001 and in 2008. The proportion of non-fossil fuel in the total energy in the pulp and paper industry was about 84.3% in 2001 and 87.0% in 2008. Only in the iron and steel industry and the stone and mineral industry was fossil fuel the primary energy. In 2008, for example, the share of fossil fuel in the iron and steel industry and the stone and mineral industry was 68.3% and 78.0%, respectively.

Table 2. Aggregated energy use by sector in 2001 and 2008

Sector	Energy (GWh)	Energy share (%)*	Fossil fuel (%)	Non-fossil fuel (%)
2001				
Total	85464		34.5	65.5
Pulp and paper	35781	41.9	15.7	84.3
Basic iron and steel	16476	19.3	69.9	30.1
Chemicals	8306	9.7	38.6	61.4
Mining	4738	5.5	39.3	60.7
Stone and minerals	4350	5.1	74.8	25.2
Wood products	4301	5.0	6.0	94.0
Food	3754	4.4	45.4	54.6
Motor vehicles	3002	3.5	26.9	73.1
Machinery	2059	2.4	21.0	79.0
Electro	832	1.0	21.5	78.5
Rubber and plastic	784	0.9	31.3	68.7
Fabricated metal products	531	0.6	30.7	69.3
Textiles	337	0.4	57.3	42.7
Printing	213	0.3	27.2	72.8
2008				
Total	87200		31.8	68.2
Pulp and paper	38355	44.0	13.0	87.0
Basic Iron and steel	17483	20.0	68.3	31.7
Chemicals	5655	6.5	28.9	71.1
Mining	5589	6.4	40.5	59.5
Wood products	5316	6.1	3.3	96.7
Stone and minerals	5250	6.0	78.0	22.0
Food	3510	4.0	37.4	62.6
Motor vehicles	2453	2.8	19.5	80.5
Machinery	1510	1.7	16.6	83.4
Rubber and plastic	840	1.0	23.8	76.2
Electro	507	0.6	18.5	81.5
Fabricated metal products	386	0.4	25.4	74.6
Textiles	175	0.3	57.7	42.3
Printing	171	0.2	28.1	71.9

* the share of energy use by each sector in the overall energy use.

5.2. The DEA specification

A joint production technology is specified in model (1) that uses four inputs to produce a single desirable output and two undesirable outputs. The desirable output is the firm's final sale divided by the corresponding sector-level producer price index. The two undesirable outputs are SO_2 and NO_x. Since the amount of CO_2 produced by a firm is a linear function of the amount of fossil fuel consumed and the emission factor associated with the fuel, we choose not to include CO_2 as an undesirable output in the empirical DEA model, because we have included fossil fuel as input.[16]

The four inputs are capital, labor, fossil fuel, and non-fossil fuel. Capital and labor are non-energy inputs and will be fixed at the observed amounts in (1). Capital stock is calculated using gross investment data by using the perpetual inventory method.[17] Labor is the number of employees. Fossil fuel consists of coal, oil and gaseous fuel, while non-fossil fuel is composed of electricity, wood fuel and heat. The reason for classifying electricity into non-fossil fuel is that electricity is primarily generated by nuclear power, hydro power and wind in Sweden (Swedish Energy Agency, 2013).

5.3. The econometric model

A second-stage regression analysis follows the measurement of efficiency to assess how policy measures affect energy efficiency. The regression model corresponding to (3) is specified as:

$$\begin{aligned}\alpha_{kt} = {} & \beta_0 + \beta_1 ctax_{kt} + \beta_2 etaxpay_{kt} + \beta_3 etsfirm_{kt} + \beta_4 R\&D_{kt} + \beta_5 emix_{kt} + \beta_6 lfirm_{kt} + \\ & \gamma_1 dPAP + \gamma_2 dCHM + \cdots + \gamma_{13} dPRN + \\ & \omega_1 y2002 + \omega_2 y2003 + \cdots + \omega_7 y2008 \quad + \; \varepsilon_{kt}, \end{aligned} \tag{4}$$

where α_{kt} is the DEA efficiency estimate of firm k in year t, obtained by solving model (1).

$ctax$: The variable $ctax$ is included to capture the effect of CO_2 tax. The tax rate per kg CO_2 emitted is in principle equal to all firms. However, because many industrial firms are exempt to some degree from paying the tax, the actual rate will vary across firms. The variable $ctax$ measures the *effective* tax rate at which a firm actually paid per kg CO_2 emitted, and is constructed by dividing the actual total amount of

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[16] Statistics Sweden calculates the amount of CO_2 emission by multiplying the quantity of fossil fuel consumption by the emission factor associated with the fossil fuel. Neither CO_2 emission abatement nor capture is assumed. Zaim and Taskin (2000), and Zofio and Prieto (2001), among others, chose not to include energy as an input in their DEA models in examining the performance of CO_2 emissions.

[17] We adopted a 0.08 capital depreciation rate for all firms (see Brännlund and Lundgren, 2010).

CO_2 tax payment of a firm by the observed amount of CO_2 output of the firm. The primary objective of introducing the CO_2 tax is for reducing CO_2 emissions. The reduction can be achieved by less fossil fuel consumption due to additional cost placed on it by the tax. Still, Firms may respond by improving energy efficiency to reduce energy cost. Thus, the introduction of CO_2 tax is likely to motivate firms to more efficiently use energy. We would expect that a higher value of this variable is to be connected with a higher energy efficiency.

$etaxpay$: We may examine the effect of energy tax by specifying a variable *etax*, which measures effective energy tax rate, in a similar way to dealing with the CO_2 tax. As such, however, the problem of endogenous variable can arise. The PFE program contributes to firms' energy efficiency (see Section 3). The program is also correlated with the variable $etax$ in that a firm will pay less electricity tax if the firm has improved its energy efficiency. The effect of the program will be contained in the error term of (4), when it is ignored.[18] Consequently, the variable $etax$ will be *endogenous*. We have noted the fact that the PFE program gives a tax exemption only on electricity rather than on all types of energy, it implies that, whether or not a firm paid an energy tax is independent of whether the firm participated in the program or not. To remedy the problem of endogeneity, thus we include the binary variable $etaxpay$ rather than $etax$ to capture the effect of energy tax.[19] $etaxpay$ is equal to 1 if a firm has $etax > 0$ and 0 otherwise.

$etsfirm$: The binary variable $etsfirm$ is included to capture the effect of the EU ETS. The SCB data has a column which indicates whether a firm is covered by the EU ETS or not. $etsfirm$ is equal to 1 if a firm is in the EU ETS and 0 otherwise. Essentially, the EU ETS places a price on carbon emitted by industrial firms and thus additional cost is placed on fossil fuel. In this sense, the ETS may motivate firms to improve energy efficiency. For the same reasons as with the CO_2 tax, we would expected that, the ETS firms have, on average, higher energy efficiency, compared to the firms that are outsides the EU ETS.

R&D: The variable *R&D* is included to examine the efficiency impact of firms' R&D investment in environmental protection. R&D investments are generally assumed to have a positive impact on firms' productivity (Griliches, 1979). Griliches (1986) uses a large sample of US manufacturing firms from 1957 to 1977 to explore the relationship between R&D expenditures and productivity growth and finds that firm's R&D expenditures contributed to productivity growth in the long run.[20] In the present paper, we

[18] Not having access to data prevents us from specifying a variable to control for the program.
[19] The variable $etaxpay$ is uncorrelated with the omitted PFE program.
[20] Griliches (1986) uses accumulated R&D expenditures over time in the model, thus he examines a long-term effect of R&D investment on productivity growth.

examine the effect of firms' current R&D investment on energy efficiency, and the effect can be understood as a short-term effect. The R&D variable could have either a positive or a negative coefficient.

$emix$: The variable $emix$ is included to capture the effect of firms' energy composition. $emix$ measures the energy composition in terms of the observed amount of CO_2 relative to the amount of energy, and will have a higher value when a firm uses an energy mixture emitting more CO_2 per kWh. Energy-mix differs across firms in that the proportion of coal, oil, gas, electricity, and non-fossil fuels varies from firm to firm. Differences in energy-mix can lead to different costs and emissions per kWh energy across firms. Thus, firm's energy-mix is likely to affect energy efficiency.

$lfirm$: The binary variable $lfirm$ is included to control for the effect of firm size. $lfirm$ is equal to 1 if a firm is large and 0 otherwise. The firm size is determined according to the median value of firms' number of employees in a specific industry and in a given year. Large firms may hire more high-quality labors and invest more in technical innovation, which may positively impact on energy efficiency.

Since the energy efficiency estimates are obtained by solving the DEA model (1) for each sector and each year, the technological frontier constructed for firms differs across sectors and in different years. Thus, we arbitrarily choose the iron and steel industry as the base group, and include 13 sector dummies, $dPAP,\ dCHM, \ldots,$ and $dPRN$, to capture sector heterogeneity.[21]

Finally, the year dummy variables $y2002, y2003, \ldots,$ and $y2008$ are included to capture technical changes. The base year is 2001.

6. Results

6.1. Estimates of energy efficiency

Energy efficiency is estimated for firms by solving model (1). The production frontier is constructed from the observed data from a specific industry and from a given year. Table 3 reports the efficiency estimates by sector. Columns 1-8 present the average energy efficiency of the sample firms in each industry from 2001 to 2008. For example, in 2008, the average efficiency of the sample firms in the pulp and paper industry is 0.939, implying that it would be possible to reduce the observed amount of energy

[21] The regression analysis can be separately conducted for each sector. We choose to use a single regression instead of separate regressions for two reasons. One reason is that for some sectors, e.g., the textiles industry, there are no firms in the ETS at all. The second reason is that by separate regressions a variable's coefficient estimates may have opposite sign in different sector regression equations, thereby increasing the complexity of explaining the effect of policy measures.

consumption in this industry by 6.1% and still produce the observed amount of outputs, without requiring any additional amount of capital and labor inputs.

Table 3. Average estimates of energy efficiency by sector.

Sector	2001	2002	2003	2004	2005	2006	2007	2008	Annual Average*
Pulp and paper	0.898	0.907	0.933	0.939	0.938	0.955	0.964	0.939	0.925
Basic iron and steel	0.911	0.939	0.946	0.922	0.925	0.949	0.943	0.954	0.915
Chemicals	0.825	0.848	0.829	0.836	0.859	0.823	0.843	0.844	0.879
Mining	0.896	1.000	1.000	0.974	0.949	0.914	0.925	0.887	0.930
Wood products	0.835	0.866	0.843	0.820	0.821	0.828	0.791	0.838	0.762
Stone and minerals	0.725	0.769	0.757	0.528	0.601	0.689	0.686	0.749	0.705
Food	0.839	0.837	0.849	0.827	0.816	0.787	0.801	0.780	0.781
Motor vehicles	0.846	0.863	0.844	0.841	0.834	0.864	0.850	0.801	0.850
Machinery	0.679	0.676	0.742	0.722	0.702	0.682	0.688	0.708	0.684
Rubber and plastic	0.905	0.917	0.932	0.930	0.834	0.754	0.902	0.869	0.813
Electro	0.741	0.722	0.732	0.875	0.849	0.890	0.909	0.897	0.777
Fabricated metal	0.825	0.866	0.921	0.628	0.644	0.638	0.659	0.672	0.781
Textiles	0.935	0.915	0.922	0.926	0.903	0.923	0.922	0.904	0.911
Printing	0.944	0.951	0.997	0.914	0.888	0.900	0.910	0.950	0.890

*Annual average = geometric mean estimate of energy efficiency of the years 2001-2008.

Since the Swedish energy and climate targets are decided by using the year 2008 as the base year, we focus on the efficiency estimates obtained for 2008. The efficiency estimates in the Table 3 imply that there was potential to improve energy efficiency in the Swedish industry and the potential differs across sectors. Again, looking at the average efficiency estimates in 2008, we can find that there existed relatively large inefficiencies in firms from the stone and mineral industry, the machinery industry, and the metal products industry, and it would be possible to reduce on average the amount of energy use by the firms by 25.1%, 29.2% and 32.8%, respectively. In contrast, there were small inefficiencies in the firms from the two largest energy users, i.e., the pulp and paper industry, and the iron and steel industry, in which the energy consumption could potentially be reduced by 6.1% and 4.6%, respectively. This finding has an important policy implication. To achieve the goal of increasing energy efficiency, policy measures should not only concentrate on firms in the large energy-use industries. The firms in the small energy-use industries should also receive particular attention.

The quantity of the potential CO_2 emission reduction of firms in a given year is calculated by using (2). The total potential reduction in each sector in 2008 is presented in Figure 1. It shows that the stone and minerals industry had the largest potential reduction measured in ton, while the pulp and paper industry had the third largest potential. The main reason for this can be that the stone and minerals industry had a low energy efficiency (0.749, see Table 2) and used a large proportion of fossil fuels (78%). In contrast, the pulp and paper industry had a high energy efficiency (0.939, see Table 2), and a very low proportion of fossil fuels (13%). Thus, the potential emission reduction in the pulp and paper industry was much lower than in the stone and minerals industry, even though the former was responsible for 44% of the industrial sector's total energy use. At the entire industry level, the potential CO_2 emission reduction, when the energy inefficiencies were removed, was about 3.2%.

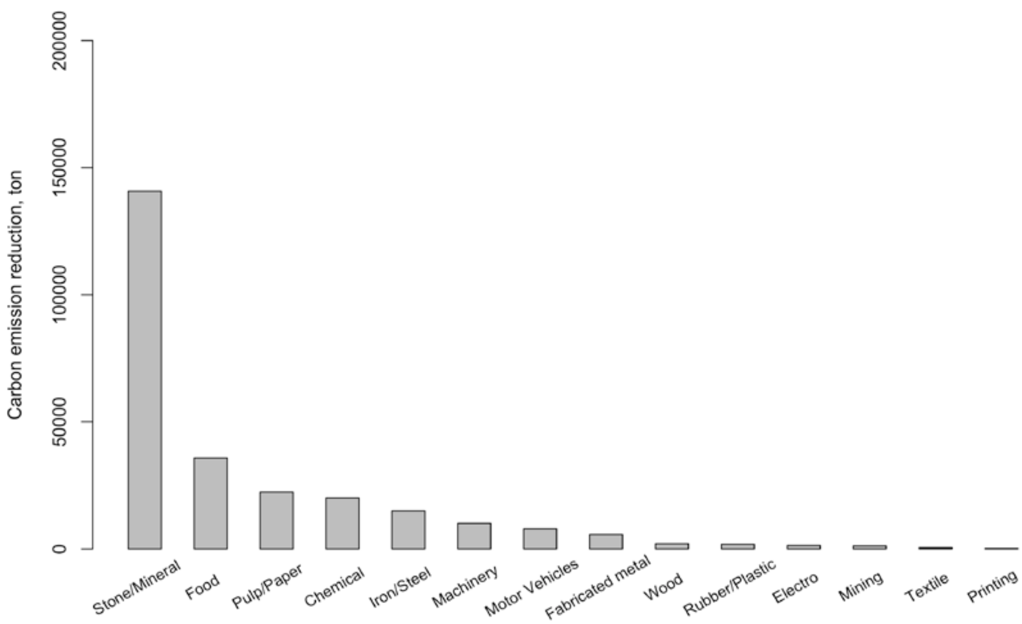

Figure 1. Potential reduction of CO_2 emissions by sector in 2008.

6.2. Assessing the effect of policy measures

The econometric model (4) is estimated by pooling the data and by applying the adapted algorithm for the double bootstrap described in Section 4.2.[22] The results from the truncated regression are reported in Table 4. Column 1 provides the coefficient estimates; Column 2 presents the 95% estimated confidence intervals.

The EU ETS has a positive but insignificant coefficient, implying that the firms included in the EU ETS did not have significantly higher energy efficiency, compared to the firms outside the EU ETS, ceteris

[22] Simar and Wilson (2007) pointed out that the number of bootstrap replications $L_1 = 100$ and $L_2 = 2000$ are sufficient for the estimation. In the present paper, we use $L_1 = 200$ and $L_2 = 2000$.

paribus. There are likely two reasons for the insignificance. The first reason is that the carbon dioxide prices created by the EU ETS in the sample period were too low to create strong incentives for improving energy efficiency. This explanation is supported by the reported permit prices. The average prices in 2005, 2006, 2007 and 2008 are SEK 232.92, 181.76, 6.17 and 195.12 per ton CO_2, respectively, which correspond to SEK 0.0604, 0.0448, 0.0016 and 0.0505 per kWh (see e.g., Lundgren et al. 2015). In other words, the ETS carbon price was not high enough to strongly motivate firms to improve their energy efficiency. This is also in line with the result provided by Lundgren et al. (2015), in which it was found that the carbon price (2005-2008) was too low to create incentives for firms' productivity development in the Swedish pulp and paper industry. The second reason for the insignificance is that the firms included in the EU ETS were concentrated in the pulp and paper industry. The average energy efficiency was over 0.90 (see Table 3), implying the variation in the efficiency estimates is small in this industry. The small variation could lead to the insignificant coefficient on the EU ETS variable. Our finding that the EU ETS had a positive but insignificant effect on energy efficiency in the sample period is consistent with the finding by Lundgren et al. (2014), in which the SFA method is applied to the same data set as the one used in the present paper.

Furthermore, the CO_2 tax has a positive but insignificant coefficient, implying the CO_2 tax did not created incentives as well. One reason is that a great number of industrial firms were exempt from paying a large part of the CO_2 tax, together with the rather low level of CO_2 tax in the sample period.

The energy tax has a positive and significant effect, implying that the firms which paid energy tax had a higher energy efficiency compared with the firms which did not pay the tax. This is to say, the energy tax had created incentives for improving energy efficiency. The reason why the energy efficiency effect of the energy tax is significant while the impact of the CO_2 tax is insignificant is likely as follows. The energy tax was paid on both fossil fuels and electricity, and electricity are responsible for about 37% of the industry energy use, while the CO_2 tax was only paid on fossil fuels

The coefficient for R&D investment is positive but insignificant, implying that the firm's R&D investment in the environmental protection did not have a significant impact on the energy efficiency. In the present paper, the R&D investment is the current expenditures spending on the environmental protection. This means that our model tests the short-term effect of the investment. In the short run, the R&D investment may not have a significant effect on the energy efficiency, even though it can be significant in the long run. Besides, the R&D investment is for environment protection, not directly on enhancing energy efficiency. Hence, the insignificant effect seems plausible.

Energy mix has a positive impact on energy efficiency and is significant, implying that the more fossil fuel the energy (which the firm uses) contains, the more efficiently the firm use the energy. The firms which use relatively more fossil fuels will make efforts to improve energy efficiency so that the cost due to CO_2 tax and/or the EU ETS can be reduced, even though this is not what we can see in the regression results, i.e., the parameters of *ctax* and *etsfirm* are not significant.

Finally, the large firm dummy has a positive and significant effect, compared with the small firms and the year dummy estimates suggest that the efficiency has a U-shaped trend over the time period studied.[23]

Table 4. Estimated parameters and confidence intervals for the regression model

	Coefficients	Confidence interval (95%)
Intercept	0.184***	(0.100, 0.213)
ctax	0.003	(-0.011, 0.021)
etaxpay	0.087***	(0.068, 0.124)
etsfirm	0.070	(0.026, 0.136)
R&D	0.001	(-0.004, 0.007)
emix	0.238***	(0.216. 0.368)
lfirm	0.022***	(0.012, 0.036)
Sector dummies, basic iron and steel sector is the base group		
Pulp and paper	-0.023	(-0.053, -0.005)
Chemicals	-0.029*	(-0.062, -0.014)
Stone and mineral	0.042***	(0.029, 0.078)
Mining	0.031	(0.005, 0.076)
Food	-0.027*	(-0.058, -0.012)
Wood products	0.110***	(0.083, 0.165)
Motor vehicles	-0.057***	(-0.101, -0.043)
Machinery	0.005	(-0.014, 0.029)
Rubber and plastic	-0.074***	(-0.128, -0.063)
Electro	0.068***	(0.059, 0.115)
Textiles	-0.036*	(-0.074, -0.022)
Fabricated metal products	-0.032*	(-0.066, -0.020)
Printing	-0.026	(-0.061, -0.008)
Year dummies, year 2001 is the base year		
$y2002$	0.017**	(0.009, 0.035)

[23] The trend is valid only when there were no technology changes.

$y2003$	0.026***	(0.021, 0.047)
$y2004$	-0.021***	(-0.041, -0.016)
$y2005$	-0.017**	(-0.034, -0.011)
$y2006$	-0.014*	(-0.030, -0.006)
$y2007$	0.008	(-0.002, 0.022)
$y2008$	-0.002	(-0.015, 0.009)
Sigma	0.197***	
Log Likelihood	2238.7	

*, **, and *** denotes the 10%, 5% and 1% significant levels, respectively.

7. Conclusions

This paper assesses energy efficiency in Swedish industry. Using unique firm-level panel data covering the years 2001-2008, efficiency estimates are obtained for firms in 14 industrial sectors by using data envelopment analysis (DEA). In the DEA model, essentially, we consider the maximum possible proportional reduction in energy inputs that still enables to produce the observed amount of outputs, without requiring any additional amount of capital and labor. Then, the impact of policy measures on energy efficiency is examined by conducting a second-stage regression analysis, and consistent estimates of the coefficients in the regression model are obtained by adopting a modified version of the double bootstrap procedure of Simar and Wilson (2007). We focus on the effect of the EU ETS, and the national level energy and carbon taxes.

We find that there was potential to improve energy efficiency in the industry in the sample period. The potential can differ across sectors. Also, we find that in small energy-use industries relatively large energy inefficiencies existed, e.g., in the stone and minerals industry and the machinery industry. This finding has an important policy implication. To achieve the goal of increased energy efficiency, policy measures should not only concentrate on firms in the large energy-use industries. The firms in the small energy-use industries should also receive particular attention.

The results from the regression analysis reveal that the EU ETS did not have a significant impact on energy efficiency in the sample period, probably due to low permit prices during the period studied. This is in line with the result by Lundgren et al. (2015), in which it was found that the carbon price (2005-2008) was too low to create incentives for firms' productivity development in the Swedish pulp and paper industry. Our results corroborates the findings in Lundgren et al. (2014), in which the SFA method is applied to the same data set as the one used in the present paper, to examine the impact on energy efficiency of the introduction of the EU ETS. Also, the results from the regression analysis show that the CO_2 tax did not have a significant effect on energy efficiency either. There are likely two reasons. One is that the large number of firms being exempt from paying the tax - to some degree - led to a low effective tax. Another reason is that, either the CO_2 tax or the EU ETS is intended to reduce carbon emission from burning fossil fuels; however, fossil fuels are only responsible for about 30% of the industry energy use. Thus, to use the EU ETS or CO_2 tax (or both) as instrument to motivate industrial firms to improve energy efficiency, the actual price which is placed on the fossil energy must be high enough so that incentives can be created.

Still, we find that the energy tax had created incentives to improve energy efficiency, probably because the energy tax was paid on both fossil fuels and non-fossil fuels. In assessing energy efficiency, the energy consists of not only fossil fuel, but also non-fossil fuels. This implies that the energy efficiency can be improved, only when both fossil fuel and non-fossil fuel are more efficiently used.

The ever-increasing national CO_2 tax and carbon allowance prices, though these climate polices are primarily designed to reduce CO_2 emissions, both can contribute to motivate for improving energy efficiency. Our findings are consistent with (and provide evidence to support) the present climate policies just mentioned in the sense of improving energy efficiency.

The policy implications drawn in the study is based on the empirical performance of Swedish industrial firms. For a more comprehensive understanding of energy efficiency effect of the EU ETS, it would be interesting to study the performance of firms in other EU member states as well. This is a topic for future research.

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Appendix

Table A. Summary statistics of variables by sector. Firm level, 2001 and 2008

Sector	Sales (MSEK)	SO_2 (ton)	NOx (ton)	Capital (MSEK)	Labor	Fossil fuel (GWh)	Non fossil (GWh)	CO_2 tax (SEK/kg)	Energy tax (SEK/kWh)	R&D (MSEK)	ETS firms
2001											
PAP	903	30	47	686	408	68	364	0.237	0.002	0.135	0
	(1531)	(57)	(93)	(1248)	(596)	(113)	(802)	(0.294)	(0.006)	(0.403)	
BIS	1272	366	213	761	610	461	198	0.103	0.001	0.097	0
	(2040)	(1779)	(979)	(1731)	(1002)	(1967)	(405)	(0.141)	(0.001)	(0.314)	
CHM	639	7	8	584	317	33	53	0.365	0.002	0.059	0
	(2258)	(30)	(22)	(2404)	(1010)	(94)	(162)	(1.311)	(0.006)	(0.289)	
MIN	673	44	182	1021	354	116	180	0.178	0.002	0.069	0
	(1628)	(132)	(648)	(2560)	(805)	(334)	(468)	(0.244)	(0.002)	(0.250)	
WOD	214	2	6	69	107	2	29	0	0	0.003	0
	(403)	(4)	(11)	(150)	(202)	(7)	(55)	(0)	(0)	(0.021)	
STN	186	7	28	89	175	47	16	0.115	0.001	0.029	0
	(223)	(34)	(179)	(156)	(230)	(206)	(48)	(0.052)	(0.002)	(0.161)	
FOD	424	1	2	128	221	10	12	0.084	0.003	0.005	0
	(872)	(4)	(4)	(251)	(498)	(21)	(25)	(0.095)	(0.006)	(0.041)	
MOT	1514	3	2	511	707	9	25	0.161	0.006	0.016	0
	(6172)	(18)	(10)	(1933)	(2300)	(31)	(82)	(0.141)	(0.006)	(0.084)	
MAC	364	0.223	0.430	90	255	2	8	0.175	0.007	0.013	0
	(913)	(0.680)	(1.016)	(231)	(510)	(5)	(20)	(0.468)	(0.020)	(0.100)	
RUB	134	0.122	1	68	114	3	7	0.057	0.001	0	0
	(186)	(0.263)	(2)	(103)	(136)	(11)	(12)	(0.099)	(0.001)	(0)	
ELE	956	0.392	0.522	79	638	2	9	0	0.009	0.035	0
	(2203)	(1.707)	(1.368)	(185)	(1195)	(7)	(18)	(0)	(0.013)	(0.168)	
MET	54	0.157	0.391	25	107	2	4	0	0	0	0
	(92)	(0.735)	(2.111)	(38)	(336)	(9)	(12)	(0)	(0)	(0)	
TEX	75	1	0.859	34	84	4	3	0	0	0.001	0
	(99)	(2)	(1.430)	(81)	(101)	(6)	(5)	(0)	(0)	(0.007)	
PRN	83	0.027	0.244	41	95	1	3	0	0	0	0
	(150)	(0.062)	(0.557)	(56)	(118)	(2)	(6)	(0)	(0)	(0)	
2008											
PAP	1189	27	54	999	388	67	451	0.167	0.001	0.177	40
	(1774)	(51)	(93)	(1612)	(527)	(114)	(881)	(0.113)	(0.002)	(0.562)	
BIS	980	269	160	712	466	351	163	0.019	0.002	0.270	7
	(1900)	(1402)	(796)	(1505)	(749)	(1603)	(315)	(0.042)	(0.002)	(1.377)	
CHM	652	3	4	573	256	19	46	0.642	0.010	0.665	11
	(2452)	(12)	(14)	(2685)	(909)	(63)	(146)	(1.244)	(0.036)	(3.028)	
MIN	627	43	192	1572	356	126	185	0.073	0.002	2.898	2
	(1879)	(141)	(740)	(4292)	(857)	(402)	(523)	(0.088)	(0.003)	(10.445)	
WOD	234	2	7	77	87	1	35	0	0.011	0.004	7
	(514)	(5)	(16)	(192)	(163)	(5)	(86)	(0)	(0.007)	(0.030)	
STN	200	7	26	84	132	45	13	0.044	0.006	0.052	14
	(296)	(31)	(163)	(146)	(194)	(192)	(45)	(0.062)	(0.001)	(0.248)	
FOD	396	1	2	144	158	6	10	0.114	0.005	0.005	5
	(1095)	(3)	(6)	(465)	(363)	(15)	(34)	(0.155)	(0.006)	(0.059)	
MOT	2133	2	1	728	587	5	21	0.756	0.009	0.072	4
	(9352)	(16)	(8)	(3390)	(2199)	(19)	(75)	(1.024)	(0.010)	(0.617)	
MAC	380	0.060	0.212	71	177	1	5	0	0.001	0.107	0
	(1395)	(0.145)	(0.506)	(203)	(460)	(2)	(15)	(0)	(0.001)	(1.329)	
RUB	140	0.088	0.384	58	93	2	6	0.498	0.004	0.003	1
	(254)	(0.254)	(0.883)	(111)	(136)	(4)	(14)	(0.863)	(0.04)	(0.016)	
ELE	1161	0.097	0.274	64	264	1	6	0	0	0.017	1
	(5157)	(0.436)	(0.926)	(162)	(1116)	(5)	(26)	(0)	(0)	(0.117)	
MET	27	0.029	0.098	14	32	0.459	1	0	0	0.066	0
	(52)	(0.122)	(0.234)	(22)	(33)	(1.019)	(3)	(0)	(0)	(0.959)	
TEX	56	0.391	0.518	34	63	2	2	0	0	0.032	0
	(79)	(1.333)	(1.076)	(94)	(117)	(5)	(3)	(0)	(0)	(0.201)	
PRN	45	0.018	0.203	31	53	1	2	0	0	0	0
	(80)	(0.034)	(0.564)	(55)	(94)	(2)	(4)	(0)	(0)	(0)	

Note: PAP = pulp and paper; BIS = basic iron and steel; CHM = chemicals; STN = stone and minerals; MIN = mining; FOD = food; WOD = wood products; MOT = motor vehicles; MAC = machinery; RUB = rubber and plastic; ELE = electro; TEX = textiles; MET = fabricated metal products; and PRN = printing.