CERE

**CERE Working Paper, 2020:1**

# A Dynamic Analysis of Industrial Energy Efficiency and the Rebound Effect

Golnaz Amjadi, Tommy Lundgren, Wenchao Zhou



SLU

UMEÅ UNIVERSITET

Department of Economics, Umeå University, S-901 87,
Umeå, Sweden www.cere.se

# A Dynamic Analysis of Industrial Energy Efficiency and the Rebound Effect[1]

Golnaz Amjadi [†1,4], Tommy Lundgren [1,2], Wenchao Zhou[1,3]

[1]Umeå University, Centre for Environmental and Resource Economics (CERE)
[2]Swedish University of Agricultural Sciences, Department of Forest Economic
[3]Umeå University, Center for regional science (CERUM)
[4]STATEC Research (National Institute of Statistics and Economic Studies)

# Abstract

Energy efficiency improvement (EEI) is generally known to be a cost-effective measure for meeting energy, climate and sustainable growth targets. Unfortunately, behavioral responses to such improvements (called *energy rebound effects*) may reduce the expected savings in energy and emissions from EEI. Hence, the size of this effect should be considered to help set realistic energy and climate targets. Currently there are significant differences in approaches for measuring rebound effect. Here, we used a two-step procedure to measure both short- and long-term energy rebound effects in the Swedish manufacturing industry. In the first step, we used data envelopment analysis (DEA) to obtain energy efficiency scores. In the second step, we estimated energy rebound effects using a dynamic panel regression model. This approach was applied to a firm-level panel dataset covering all 14 sectors in the Swedish manufacturing industry over the period 1997–2008. We showed that, in the short run, partial rebound effects exist within most of manufacturing sectors, meaning that the rebound effect decreased, but did not totally offset, the energy and emission savings expected from EEI. The long-term rebound effect was smaller than the short-term effect, implying that within each sector, energy and emission savings due to EEI are larger in the long run compared to the short run.

**JEL classification** : C02, C33, D22, Q40, Q50
**Keywords**: Energy efficiency improvement, rebound effect, data envelopment analysis.

[1] Swedish Energy Agency funded this study.

# 1 Introduction

Greenhouse gas (GHG) emissions drive climate change (Intergovernmental Panel on Climate Change, 2013) and about 60% of these are generated by energy use (International Energy Agency, 2020). Therefore, global attempts to reduce GHG emissions and combat climate change have aimed to reduce energy use.[2]

Energy efficiency improvement (EEI) is generally recognized as a cost-effective measure for reducing energy use. EEI can be achieved if either the same level of goods and services are produced using less energy, or if more goods and services are produced using the same level of energy. Improving energy efficiency should decrease the real unit price of energy service for an industrial firm. This change can initiate a re-optimization response that can appear in the form of substitution and output effects. This response is called the *energy rebound effect*, and may ultimately mitigate, increase, or even reverse the energy and emission savings expected from EEI. Hence, if the aim is to improve overall energy efficiency (with the ultimate goal of ameliorating climate effects), it is essential to understand the size and scope of the rebound effect.

According to Saunders (2000), measuring the energy rebound effect ought to be straight forward, requiring only an estimate of the elasticity of demand for energy services[3] with respect to changes in energy efficiency. In practice, however, estimating this elasticity is not so simple, and empirical studies have used different methods to measure the energy rebound effect, with no clear consensus yet about what method(s) might be best. Each of these methods have limitations and drawbacks. For instance, one group of studies estimated the rebound effect indirectly through estimating price elasticities of energy demand (e.g., Bentzen, 2004; Saunders, 2013, Dahlqvist et al., 2020). These estimates provided proxies for the rebound effect but were potentially biased for two reasons (Sorrell et al., 2009). First, the energy rebound effect is a consumer's behavioral response to a decrease in real unit price of energy service, whereas price elasticities of demand are usually estimated for periods with increasing energy prices. Using such elasticities potentially overestimates the size of the energy rebound effect, because energy demand responds more strongly to price increases than price decreases (see e.g. Bentzen, 2004; Dahlqvist et al., 2020). Second, as opposed to energy price changes (which in most cases are exogenous), behavioral responses to EEI are driven endogenously by investments to replace

[2] For instance, there is a target to reduce global energy intensity, i.e. the ratio of energy use per unit of output, by 40% by 2030 (United Nation Secretary General`s Advisory Group on Energy and Climate Change, 2010). A lower energy intensity implies that less energy is used to produce one unit of output, and is therefore desirable in this context.

[3] Economists generally define energy services as useful work (Ayres and Ayres, 2010). Alternatively, energy services can be defined as the effect or outcome of using an energy flow, for example, the heating of a room to a particular temperature or the transportation of something over a certain distance within a certain time (Baumgartner and Midttun, 1987).

the less efficient technology. Taking the price elasticity of demand as a proxy for energy rebound effect implies that such investments are exogenous, which they are not.

An alternative way to approach this problem was proposed by Orea et al. (2015), who integrated the measurement of rebound effect into a stochastic energy demand frontier model and estimated the effect according to the more theoretically sound definition suggested by Saunders (2000). This approach gave a direct measure of the energy rebound effect and avoided the problems of using the price elasticities as proxies. To obtain such a measure, they modified the conventional stochastic energy demand frontier model by adding an interaction term (i.e. a parameterized rebound function) with the inefficiency term, thereby estimating energy efficiency and the energy rebound effect simultaneously in a one-step procedure. Amjadi et al. (2018) adopted this approach for estimating the rebound effect for four energy-intensive sectors in the Swedish manufacturing industry. However, this approach had some limitations. First, it measured the rebound effect only through its determinants, and therefore may have been biased due to some omitted variables. Second, it precluded the existence of two potential types of rebound outcomes ("backfire" and "full rebound", see discussion below) due to the one-sided nature of the inefficiency term in the stochastic frontier analysis (SFA) models, and the true size of the rebound effect might have been under-estimated. Finally, convergence properties were also very sensitive to the variables included in the rebound function.

In another approach, Adetutu et al. (2016) adopted a two-stage strategy for measuring the energy rebound effect. In the first stage, they used SFA to measure the energy efficiency scores. In the second stage, they estimated a dynamic energy demand regression model in which various variables interacted with the energy efficiency term. The drawback to their approach, and to all parametric approaches in general, is that a functional form for the production technology must be assumed. In addition, Adetutu et al. (2016) did not estimate the rebound effect and efficiency scores simultaneously in a one-step procedure, and therefore their estimates are less efficient than Orea et al. (2015) or Amjadi et al. (2018).

In this paper, we suggest a two-stage approach for measuring the energy rebound effect. The motivation for our empirical approach is to overcome the limitations and drawbacks of the previously mentioned approaches. In the first stage, we use data envelopment analysis (DEA) to obtain technical energy efficiency scores. In the second stage, a dynamic panel data regression model is used to measure the elasticity of energy demand with respect to changes in energy efficiency.

Our contribution to the empirical research about the energy rebound effect can be summarized as follows. Applying DEA in the first stage allowed us to account for bad outputs (emissions) when measuring energy efficiency scores, and it did not require specifying any parametric production technology.

Furthermore, using a dynamic panel regression model in the second stage allowed for measuring both short- and long-term rebound effects. Finally, the approach allowed for all possible (known) rebound effects.

The rest of this paper is structured as follows. Section 2 introduces the concept of energy rebound effects and its driving mechanisms, as well as empirical studies about the producer-side rebound effect. Sections 3 and 4 present the empirical framework and describe the data used, respectively. Section 5 presents the results and gives policy guidelines based on post-estimation calculations, and in section 6 we conclude.

# 2 The Rebound Effect: Mechanisms and Empirical Literature Review

This section gives a short background about the energy rebound effect and the underlying mechanisms, which is then complemented by a literature review focusing on empirical studies that measure the energy rebound effect for the production side of the economy.

## 2.1 Background and Mechanisms

As long ago as the middle of the 19$^{th}$ century, the William Stanley Jevons noticed that the invention of more efficient steam engines increased industrial use of coal. This phenomenon became known as "Jevons paradox". Later, Khazzoom (1980) assigned the term energy rebound effect to this paradox in the economic literature.

"Production-side energy rebound effect" refers to a producer's behavioral changes in energy use that have been induced by energy use becoming more efficient. Two effects drive this change, namely the substitution/intensity effect and the output effect (see e.g., Saunders, 1992; Saunders, 2008). EEI increases the energy productivity, meaning that more output can be produced using the same level of energy input. The real unit price of energy service decreases and, hence, the price of energy (relative to other inputs) also falls. Producers may, to some extent, substitute energy for other inputs, and when this happens it is called the *substitution/intensity effect*. Cost savings due to the substitution effect might then be used for scaling up production levels, which in turn increases energy use, and this increase is called the *scale/output effect*. These two effects determine the size of the *energy rebound effect*, which is defined as the difference between the actual energy savings and the expected energy saving from EEI that had been calculated from an engineering point of view. The size of the rebound effect depends on the elasticities of substitution and productivity gains (Greening et al., 2000). The energy rebound effect is a re-optimization response to changes in relative input prices and cost savings, and it creates economic value; in that sense, it enhances the level of welfare (Borenstein, 2015). That said, the size of the rebound effect should be considered when policies addressing climate change and energy demand are set, or when the effectiveness of energy efficiency policies are evaluated.

There are three types of rebound effects: (i) a direct effect, (ii) an indirect effect, and (iii) an economy-wide effect (Greening et al., 2000). The direct effect is initiated when producers re-optimize their demand for inputs as energy becomes relatively cheaper. This re-optimization may, in general, lead to an increase in energy consumption. The indirect effect is linked to scaling up the production level due to cost savings from EEI. The economy-wide effect may occur if the direct and the indirect effects are large. The size of the energy rebound effect will fall within the range of the five scenarios presented in Table 1, namely, *backfire*, *full rebound*, *partial rebound*, *zero rebound*, and *super-conservation* (see e.g., Greening et al., 2000).

Table 1. Possible scenarios for the size of energy rebound effect (RE) and energy savings

| **Scenario** | **Size** | **Energy saving** |
|---|---|---|
| Backfire | RE > 100% | Negative energy saving |
| Full rebound | RE = 100% | Zero energy saving |
| Partial rebound | RE < 100% | Actual energy saving < Expected energy saving |
| Zero rebound | RE = 0% | Actual energy saving = Expected energy saving |
| Super-conservation | RE < 0% | Actual energy saving > Expected energy saving |

## 2.2 Empirical Studies on Producer-side Rebound Effect

Measuring the size of the rebound effect may seem straightforward, because in principle it only requires the elasticity of demand for energy services with respect to changes in energy efficiency (Saunders, 2000). In practice, data about demand for energy services and/or energy efficiency is usually lacking, which means that elasticity cannot be estimated directly (Sorrell et al., 2009; Orea et al., 2015). Instead, most empirical studies have used other elasticities as a proxy for the energy rebound effect (Sorrell and Dimitropoulos, 2008). The majority of these studies have looked at consumer-side rebound effect because data for measuring these elasticities are readily available. Few studies have tried to measure the size of the energy rebound effect for producers. Nadel (1993) reviewed a small sample of existing studies and concluded that the energy rebound effect accounted for about a 2% less than expected savings, on average, due to scaling up the production level (the output effect).

A few more recent studies have tried to estimate producer-side energy rebound effects by estimating various elasticities as proxies for the direct rebound effect. In one such study, Bentzen (2004) estimated an energy-price elasticity using a system of factor demand equations. He used data on the U.S. manufacturing sector from 1949 to 1999 and estimated an upper bound of 24% for the direct rebound effect. Another example is Saunders (2013), who measured short- and long-term direct rebound effects for 30 U.S. sectors from 1960 to 2005 by estimating the elasticity of substitution between energy and other production factors, assuming no technological gains after 1980. He concluded that the overall sector average short- and long-term direct rebound effects were about 125% (backfire) and 60% respectively.

There are a few studies measuring the direct energy rebound effects using data from China. Lin and Li (2014) estimated the direct rebound effects for heavy industry through a system of cost share equations derived from a translog cost function, resulting in a direct rebound effect of about 74%. Lin and Xie (2015) looked at the direct rebound effect for China's food production industry by estimating a system of cost share equations, resulting in a rebound effect of about 34%.

Two other studies estimated the rebound effect for Sweden's heavy industrial sectors *Pulp and paper*, *Basic iron and steel*, *Chemical* and *Mining*. Amjadi et al. (2018) used a stochastic energy demand frontier model to estimate fuel and electricity rebound effects using a firm-level panel dataset for the period 2000–2008, finding that the average fuel rebound effect was 58–65%, while the average electricity rebound effect was 76–86%. Dahlqvist et al. (2020) also estimated electricity and fuel rebound effects using a factor demand model approach and a firm-level dataset. Their estimates of electricity rebound effects showed a backfire response, while the fuel rebound effect were 24–80% across the four energy intensive sectors. Methodological differences between these two studies mean that their results are complementary — Amjadi et al. (2018) focused on movement towards the energy efficiency frontier, while Dahlqvist et al. (2020) were looking at energy-related technological changes that were moving the frontier itself.

The economy-wide rebound effect is usually measured using computable general equilibrium (CGE) models, where the estimates range from partial rebound to backfire (see e.g., Grepperud and Rasmussen, 2004; Washida, 2004; Allan et al., 2007; Vikström, 2008; Hanley et al., 2009; Broberg et al., 2015).

In summary, studies on producer-side rebound effect show a wide range of rebound effects from partial to backfire. These results are however not always comparable to each other because of differences in methods, data and definitions (Gillingham et al., 2014; Orea et al., 2015).

# 3 Methodology

Following Saunders (2008), we define the producer-side rebound effect ($R$) as:

$$R = 1 + \eta \tag{1}$$

where $\eta$ represents the elasticity of demand for energy ($E$) with respect to energy efficiency improvement (EEI), i.e., $\eta = dlnE/dlnEEI$. Instead of estimating an elasticity as a proxy for $\eta$ (as most previous studies have done), we directly estimate $\eta$ and the rebound effect using a two-stage approach. In the first stage, energy efficiency scores are calculated using DEA, while in the second stage energy demand is modelled using a dynamic panel data regression (including the first-stage energy efficiency scores), allowing estimation of both short- and long-term energy rebound effects.

## 3.1 Measuring Energy Efficiency by a Joint Production Technology

Ever since the groundbreaking work of Debreu (1951) and Farrell (1957), efficiency has been measured using different approaches and techniques. One general approach (e.g., Färe et al. 1985; Färe and Grosskopf, 2004) uses the linear programming technique DEA, which does not require specifying a functional form for the production function (i.e., no particular relationship between inputs and outputs) nor any assumptions about the distribution of efficiency scores.

We applied DEA to measure the input technical efficiency scores at firm-level. The scores indicated the maximum feasible proportional reduction of all inputs (energy and non-energy inputs) while still producing given levels of outputs. We followed the approach proposed by Färe and Grosskopf (2004), called the joint production framework, where the production of desirable outputs creates undesirable outputs. Desirable outputs are marketed goods, while undesirable outputs are by-products with negative effects on the environment and humans. This framework has two main assumptions. First, it is assumed that the production of desirable outputs always generates undesirable outputs (this is called the null-joint assumption). Given the joint production of desirable and undesirable outputs and a constant bundle of inputs, it is further assumed that any reduction in undesirable outputs is conditional on a proportional reduction of desirable outputs, implying that the disposal of undesirable outputs is costly (this is called the weak disposability assumption). This framework has the advantage that it allows one to take into account the production of undesirable outputs when evaluating the efficiency of units such as firms. Indeed, it credits firms for their abatement activities while measuring efficiency.

Setting up the linear programming model to measure efficiency scores proceeded like this. First, there are $k = 1, \dots, K$ individual firms in a sector. For each firm, there are $n = 1, \dots, N$ inputs $x$ including energy and non-energy inputs, and $m = 1, \dots, M$ desirable outputs $y$, and and $j = 1, \dots, J$ undesirable outputs $u$. Next, an assumption on the return to scale of the production technology is the minimal requirement within the DEA framework. In this paper, we assumed a constant return to scale technology. Under these assumptions, the linear programming problem to obtain the Farrell type of input technical efficiency scores ($\alpha_{k'}$) for firm $k'$ was:

$$
\begin{aligned}
\alpha_{k'} = & \min_{z_1, z_2, \dots, z_k, \alpha} \alpha \\
s.t. \quad & \textstyle\sum_{k=1}^{K} z_k y_{km} \geq y_{k'm}, \\
& \textstyle\sum_{k=1}^{K} z_k u_{kj} = u_{k'j}, j = 1, \dots, J \\
& \textstyle\sum_{k=1}^{K} z_k x_{kn} \leq \alpha x_{k'n}, n = 1, \dots, N \\
& z_k \geq 0, k = 1, \dots, K
\end{aligned}
\tag{2}
$$

where $z$ is referred to as an intensity variable and only takes a non-negative real number for each firm; this variable defines the extent to which each firm contributes to constructing the production frontier. $\alpha$ is included on the right-hand side of the input constraints and measures the technical efficiency in use of inputs, holding the level of desirable and undesirable outputs constant. $\alpha$ can have values from 0 to 1, where 1 implies full technical efficiency in use of inputs, meaning that no proportional reductions in the bundle of inputs are feasible given the level of desirable and undesirable outputs. The inclusion of the second constraint in Eq. (2) implies that we consider the production of undesirable outputs when evaluating technical efficiency in the use of inputs, which improves the analysis because it appropriately credits firms for their abatement activities. For comparison, these scores are also calculated without constraints on undesirable outputs (see Appendix for the results).

DEA-based point estimates of energy efficiency scores obtained from Eq. (2) are based on a finite sample of firms, and are necessarily affected by sampling variation because the distances to the frontier will be underestimated if the best performing firms in the population are not included in the sample (Simar and Wilson, 1998). We therefore followed the bootstrapping approach proposed by Simar and Wilson (1998) which constructs confidence intervals for DEA energy efficiency scores. This approach used the output from Eq. (2) to simulate a true sampling distribution of efficiency scores. A new dataset was created, and energy efficiency scores were calculated using this dataset. This process was repeated many times in order to obtain a good approximation of the true distribution of the sampling. The bootstrapping procedure can be summarized as follows:

1) Use DEA to calculate the energy efficiency scores using Eq. (2).
2) Draw with replacement from the empirical distribution of energy efficiency scores.
3) Divide the original efficiency input levels by the pseudo-efficiency scores drawn from the empirical distribution to obtain a bootstrap set of pseudo-inputs.
4) Apply DEA using the new set of pseudo-inputs and the same set of outputs and calculate the bootstrapped efficiency scores.
5) Repeat steps 2–4 and use bootstrapped scores for statistical inference and hypothesis testing.
The outcome of this process is a bias-corrected $\widehat{\alpha_k}$ for $\alpha_k$.

## 3.2 Measuring the Rebound Effect within a Dynamic Panel Data Regression Model

In the second stage, we use a dynamic panel data regression to model energy demand. We use the bias-corrected energy efficiency scores from the first stage as a regressor to estimate both the short- and long-term elasticities of demand for energy with respect to EEI.

For a cost-minimizing firm, the energy demand is a function of the output level, the relative price of other inputs to energy, and the level of energy efficiency. Assuming a Cobb-Douglas production technology with inputs labor, capital and energy, our dynamic energy demand regression model is written as:

$$ln\,E_{kt} = \beta_1 ln\,E_{k,t-1} + \beta_2 ln\,Y_{kt} + \beta_3\, ln\,RPCE_{kt} + \beta_4\, ln\,RPLE_{kt} + (\gamma_0 + \sum \gamma x_{kt}) ln\,EF_{kt} + \boldsymbol{\omega}_k + \boldsymbol{D}_t + v_{kt} \tag{3}$$

where

$$\sum \gamma x_{kt} = \gamma_1 DECS_{kt} + \gamma_2 EP_{kt} + \gamma_3 DFS_{kt}$$

Subscripts $k$ and $t$ represent firm and year, respectively. The dependent variable $E$ denotes energy demand and is treated as a long run equilibrium (see e.g., Adetutu et al., 2016). $\beta$s and $\gamma$s are vectors of parameters to be estimated. $E_{k,t-1}$ is the lagged energy demand and indicates the dynamic characteristic of the model by accounting for intertemporal serial correlation. Because energy demand in any current period is expected to be correlated with energy demand in a past period, we expect a positive sign for $\beta_1$. $Y$ is the quantity of output produced and it is expected to have a positive effect on the energy demand. *RPCE* and *RPLE* are the relative price of capital and labor to the energy price, respectively, and they could affect energy demand either positively or negatively, depending on whether capital/labor and energy are substitutes or complements. *EF* is the bias-corrected energy efficiency score obtained from DEA. The estimated coefficient of this variable shows the elasticity of energy demand with respect to changes in energy efficiency and therefore can be used to estimate the energy rebound effect according to Eq. (1). As can be seen, this coefficient is modeled as a function of a constant term and a few firm-specific and policy-related variables, which allows us to differentiate responses to EEI due to heterogeneity of firm-specific characteristics. The variables are (i) a dummy variable for energy cost share (*DECS*) to distinguish firms with potentially high cost savings due to EEI, (ii) the energy price (*EP*) to study the effects of energy price level and variation on the energy rebound effect[4], and (iii) a dummy variable for firm size (*DFS*) to study whether the rebound effect differs between large and small firms. For each firm in each year, the dummy variable *DECS* takes the value 1 if energy cost share of that firm is larger than the median of the sector to which the firm belongs for that year, otherwise this value is 0. In a similar manner, dummy variable *DFS* takes the value 1 if the output level is larger than the median of the sector for that year, otherwise it is 0. These variables interact with *EF* and allow us to evaluate how the energy rebound effect changes with these variables. The term $\boldsymbol{w}_k$ controls for unobserved firm's heterogeneity, while $\boldsymbol{D}_t$ is a set of year dummies controlling for year-specific effects. $\boldsymbol{v}_{kt}$ is the independent and identically distributed error term with mean zero and a constant variance, i.e. $v_{it} \sim N(0, \sigma^2)$.

Eq. (3) was estimated separately for each of the 14 sectors in the Swedish manufacturing industry using the system generalized method of moments (*GMM*) estimator developed by Arellano and Bover (1995). The estimator deals with issues related to dynamic panel data regression models, such as correlation between the lagged dependent variable and the unobservable fixed effects, endogeneity and serial correlation (for detailed information about system *GMM* see, e.g. Roodman, 2009). For each firm and year, we can obtain both short run and long run elasticities of energy demand with respect to changes in energy efficiency as:

$$\begin{aligned} &Short\ run\ \eta_{kt} = \gamma_0 + \gamma_1 DECS_{kt} + \gamma_2 EP_{kt} + \gamma_3 DFS_{kt} \\ &Long\ run\ \eta_{kt} = (\gamma_0 + \gamma_1 DECS_{kt} + \gamma_2 EP_{kt} + \gamma_3 DFS_{kt})/1 - \beta_1 \end{aligned} \tag{4}$$

Substituting these elasticities in Eq. (1) provides short- and long-term rebound effects (see also Adetutu et al., 2016, for a similar approach). Both the sign and the magnitude of these elasticities determine the range of the energy rebound effect from backfire to super-conservation. Unlike the one-stage SFA approaches proposed by Orea et al. (2015), this dynamic two-stage approach allows for all possible sizes of the rebound effects.

[4] This price also serves as a policy variable, because policy aimed at reducing energy use or mitigating emissions is likely to affect the price of energy.

# 4 Data

We used a firm-level (unbalanced) panel data set covering all sectors in the Swedish manufacturing industry from 1997–2008. The fourteen sectors are *Basic iron and steel*, *Chemical, Electro*, *Fabricated metal products*, *Food*, *Machinery*, *Mining*, *Motor vehicles*, *Printing*, *Pulp and paper*, *Rubber and plastic*, *Stone and mineral*, *Textiles*, and *Wood*. The dataset was provided by Statistics Sweden and includes firm-level information on inputs, outputs and various emissions. Descriptive statistics for an average firm and year are presented in Table 2. All variables with monetary units are based on 2008 prices measured in Swedish Crowns (SEK).

The production inputs were capital, labor and energy. The capital stock was calculated by the perpetual inventory method using gross investment data (excluding investments in buildings). The capital depreciation rate was set to 0.087 for all firms and sectors in this study as suggested in King and Fullerton (1984) and Bergman (1996). Labor was the number of employees. Energy was the sum of electricity, district heating, wood fuel, coal, solid fuel, and gaseous fuel, and were all converted to energy equivalents (GWh) by Statistics Sweden using the same conversion rates for all sectors.

The desirable output for each firm and year were calculated as the final sales divided by its corresponding producer price index for a given sector and year. The undesirable outputs were sulfur dioxide (SO2) and nitrogen oxide (NOx) measured by the metric ton.[5] The capital price was defined as the user cost of capital and calculated based on national and sector-level indices (Lundgren, 2010; Brännlund and Lundgren, 2010). Unit prices of labor (i.e. salary) and energy prices were calculated as the ratio of these input costs to the quantities used.

[5]Statistics Sweden computes CO2 emission by multiplying fuel consumption by an emission factor associated with fuel. The DEA framework in this paper allows for maximum proportional reduction of all inputs including energy while keeping both desirable and undesirable outputs constant. Hence, inclusion of CO2 as bad output is inappropriate because reduction of energy input implies reduction of CO2 and makes us deviate from the DEA framework by not holding the undesirables constant.

Table 2. Descriptive statistics for an average firm and year from 1997–2008

| Sector | Obs. | Capital (MSEK) | Labor (number) | Energy (GWh) | Output (MSEK) | SO2 (ton) | NOx (ton) | Capital price (index) | Salary (TSEK) | Energy price (SEK/MWh) |
|---|---|---|---|---|---|---|---|---|---|---|
| Basic iron and steel | 410 | 535 | 528 | 676 | 1148 | 438.1 | 238.0 | 0.12 | 702 | 554 |
| Chemical | 1201 | 398 | 276 | 88 | 627 | 9.5 | 9.0 | 0.09 | 641 | 496 |
| Electro | 1227 | 79 | 376 | 7 | 1333 | 0.2 | 0.3 | 0.10 | 346 | 380 |
| Fabricated metal products | 2193 | 11 | 43 | 2 | 30 | 0.1 | 0.1 | 0.08 | 451 | 604 |
| Food | 2553 | 130 | 200 | 23 | 427 | 1.6 | 2.6 | 0.10 | 450 | 498 |
| Machinery | 3506 | 58 | 179 | 7 | 266 | 0.2 | 0.3 | 0.09 | 460 | 520 |
| Mining | 288 | 566 | 265 | 204 | 494 | 30.0 | 127.1 | 0.12 | 663 | 614 |
| Motor vehicles | 1218 | 508 | 590 | 27 | 1601 | 2.2 | 1.8 | 0.08 | 392 | 458 |
| Printing | 920 | 30 | 73 | 4 | 64 | 0.1 | 0.3 | 0.08 | 500 | 522 |
| pulp and paper | 1019 | 722 | 397 | 433 | 1001 | 32.2 | 48.2 | 0.09 | 459 | 351 |
| Rubber and plastic | 1349 | 46 | 90 | 8 | 111 | 0.2 | 0.5 | 0.09 | 463 | 506 |
| Stone and mineral | 1019 | 75 | 151 | 56 | 178 | 7.5 | 23.8 | 0.08 | 538 | 485 |
| Textile | 749 | 31 | 79 | 8 | 68 | 0.8 | 1.0 | 0.07 | 352 | 453 |
| Wood | 3131 | 50 | 78 | 25 | 191 | 1.4 | 5.0 | 0.12 | 407 | 300 |

# 5 Results

Here, we present sector-level averages of energy efficiency scores obtained from the DEA model, followed by parameter estimates for the dynamic energy demand model. The sector-level averages of the short- and long-term energy rebound effects are presented, followed by conclusions that provide a guide to policy makers by identifying sectors where promoting EEI benefited the industry or the environment.

## 5.1 Energy Efficiency Scores from the DEA Model

Table 3 shows sector-level averages of energy efficiency scores obtained from the DEA model in Eq. (2) for all 14 sectors of Swedish manufacturing industry. These averages were calculated for the bias-corrected firm-level energy efficiency scores taking into account the production of undesirable outputs, meaning that firms are credited for their abatement activities while measuring energy efficiency.

Table 3 lists sectors according to their sector-level average energy efficiency scores, meaning that the farther one reads down the table, there is a larger potential for EEI.[6] The efficiency score is a relative measure and Table 3 indicates how firms within one sector perform on average relative to best practices available. For instance, on average, firms in the most efficient sector, *Pulp and paper*, perform closer to their best practice peers than do firms in any other sector.[7]

[6] For comparison, a corresponding table with bad outputs excluded is shown in Table 3A in the Appendix.

[7] Note that firms in different sectors do not have exactly the same technology. Thus, ranking sectors based on their average efficiency scores is not adequate because it may be easier in some sectors to perform closer to the firms defining the frontier compared to other sectors.

Table 3. Sector-level energy efficiency scores (including bad outputs)

| Sector | Average Efficiency Score | Minimum | Maximum | Std. Dev |
|---|---|---|---|---|
| Pulp and paper | 0.72 | 0.19 | 0.96 | 0.16 |
| Basic iron and steel | 0.70 | 0.21 | 0.99 | 0.19 |
| Printing | 0.67 | 0.12 | 0.97 | 0.2 |
| Wood | 0.67 | 0.09 | 0.96 | 0.2 |
| Chemical | 0.64 | 0.10 | 0.93 | 0.19 |
| Textile | 0.64 | 0.14 | 0.92 | 0.18 |
| Mining | 0.63 | 0.21 | 0.96 | 0.19 |
| Motor vehicles | 0.57 | 0.14 | 0.92 | 0.19 |
| Stone and mineral | 0.56 | 0.11 | 0.91 | 0.2 |
| Food | 0.56 | 0.11 | 0.94 | 0.19 |
| Rubber and plastic | 0.54 | 0.10 | 0.92 | 0.2 |
| Electro | 0.54 | 0.10 | 0.92 | 0.2 |
| Fabricated metal products | 0.53 | 0.06 | 0.93 | 0.19 |
| Machinery | 0.46 | 0.07 | 0.91 | 0.18 |

## 5.2 The Dynamic Energy Demand Model

Table 4 presents the results of estimating Eq. (3) using a system *GMM* estimator.[8] System GMM is an appropriate estimator for this study since our dataset covers a relatively small number of time periods and a relatively large number of firms in each sector (Roodman, 2009). Our estimates all passed the Sargan/Hansen test for the joint validity of the set of instruments as well as AR(1) and AR(2) tests. To determine the lag order of instruments for each sector, we applied the model and moment selection criteria proposed by Andrews and Lu (2001).[9]

Our coefficient estimates of the lagged dependent variable showed statistically significant and positive effects on energy demand, as expected, within all sectors. The results, where statistically significant, also suggested that the energy demand increased by the output level, which is expected. The coefficient estimates of relative price of capital and labor to the energy price were mostly positive, where significant, implying that capital/labor and energy were substitutes in general.

As mentioned earlier, the elasticity of energy demand with respect to changes in energy efficiency is modeled as a function of a constant term and a few policy-relevant and firm-characteristic variables. The constant term was statistically insignificant in most sectors. The coefficient estimates of the interaction term *DECSlnEF* were, in most sectors, statistically significant and negative, indicating that in each sector, the rebound effect was lower among firms

[8]For comparison, Table 4A in the Appendix shows a corresponding table excluding bad outputs.
[9] In our empirical estimation, the number of lags as instruments is not the same in all sectors.

with higher energy cost share, implying less pronounced adaptation and behavioral responses among such firms. The coefficient estimates of the interaction term *EPlnEF* were very small, and statistically insignificant in most sectors, suggesting that the rebound effect did not vary with the energy price in those sectors. Furthermore, the estimated coefficients of *DFSlnEF* were in most of sectors insignificant, implying that the rebound effect did not depend on the firm size, *ceteris paribus*. The coefficient estimates of the lagged energy demand imply that there is a difference between short- and long term rebound effects.

Table 4. Parameter estimates for the dynamic energy demand model by system GMM (including bad outputs)

| Sector | *lag(ln(E), 1)* | *lnY* | *lnRPCE* | *lnRPLE* | *lnEF* | *DECSlnEF* | *EPlnEF* | *DFSlnEF* | *Hansen test* | *AR1* | *AR2* | *df* | *Firms* | *Obs.* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Basic iron and steel | 0.88*** | 0.09 | 0.14 | 0.05 | -0.23 | 0.12 | 0.00 | -0.21 | 1 | 0.03 | 0.90 | 71 | 40 | 281 |
| Chemical | 0.85*** | 0.14*** | 0.13 | 0.14 | 0.16 | -0.35*** | -0.00 | 0.02 | 0.19 | 0.03 | 0.28 | 71 | 131 | 810 |
| Electro | 0.67*** | 0.25*** | -0.03 | 0.20* | 0.15 | -0.40*** | 0.00 | -0.08 | 0.53 | 0.03 | 0.16 | 70 | 170 | 809 |
| Fabricated metal products | 0.69*** | 0.23*** | 0.50*** | -0.15* | 0.13 | -0.33*** | -0.00 | -0.03 | 0.24 | 0.00 | 0.53 | 70 | 323 | 1424 |
| Food | 0.73*** | 0.22*** | -0.02 | 0.22** | -0.15 | -0.28*** | 0.00** | 0.05 | 0.54 | 0.00 | 0.50 | 71 | 304 | 1721 |
| Machinery | 0.80*** | 0.15*** | -0.01 | 0.08* | -0.12** | -0.18*** | 0.00*** | -0.01 | 0.13 | 0.00 | 0.18 | 61 | 501 | 2605 |
| Mining | 0.86*** | 0.17 | 0.34 | -0.36 | -0.87 | -0.34 | 0.00* | -0.02 | 1 | 0.06 | 0.48 | 71 | 41 | 226 |
| Motor vehicles | 0.74*** | 0.23*** | 0.35** | -0.05 | 0.00 | -0.26*** | 0.00 | -0.03 | 0.22 | 0.00 | 0.13 | 71 | 169 | 962 |
| Printing | 0.45*** | 0.51** | 1.14 | -0.56 | 0.78 | -0.61*** | -0.00 | -0.29 | 0.99 | 0.07 | 0.43 | 61 | 102 | 406 |
| Pulp and paper | 0.80*** | 0.20*** | 0.13 | 0.28** | 0.32* | -0.72** | -0.00* | 0.28* | 0.18 | 0.00 | 0.86 | 71 | 111 | 859 |
| Rubber and plastic | 0.70*** | 0.25*** | 0.16 | 0.08 | -0.09 | -0.27*** | 0.00 | -0.07 | 0.34 | 0.00 | 0.48 | 71 | 169 | 891 |
| Stone and mineral | 0.68*** | 0.28*** | 0.39** | 0.38*** | 0.40** | -0.41*** | -0.00** | -0.09 | 0.62 | 0.00 | 0.18 | 71 | 138 | 799 |
| Textile | 0.86*** | 0.13** | 0.11 | 0.11 | -0.00 | -0.24** | 0.00 | 0.12 | 0.99 | 0.00 | 0.60 | 71 | 104 | 537 |
| Wood | 0.62*** | 0.30*** | 0.45** | 0.06 | -0.07 | -0.54*** | 0.00 | -0.04 | 0.12 | 0.00 | 0.71 | 71 | 284 | 1396 |

***, **, and * indicate 1%, 5% and 10% significance levels, respectively.

## 5.3 Rebound Effect Estimates

To obtain estimates of the short- and long-term rebound effects for each firm and year, we used our coefficient estimates in Table 4 and calculated the short- and long-term firm-level elasticities defined by Eq. (4). Finally, we use Eq. (1) to estimate the short- and long-term rebound effects for each firm in each year. Using these estimates in each sector, we can obtain the sector-level averages of the short- and long-term energy rebound effects presented in Table 5.[10]

Table 5. Summary statistics of sector-level averages of the short- and the long-run rebound effects (including bad outputs)

| Sector | Short term rebound effect | | | Long term rebound effect | | |
|---|---|---|---|---|---|---|
| | Average | Min. | Max. | Average | Min. | Max. |
| Basic iron and steel | 0.90 | 0.58 | 1.23 | 0.18 | -2.55 | 2.94 |
| Chemical | 0.85 | 0.45 | 1.14 | 0.03 | -2.26 | 1.94 |
| Electro | 0.93 | 0.67 | 1.22 | 0.79 | 0.00 | 1.65 |
| Fabricated metal products | 0.87 | 0.60 | 1.12 | 0.59 | -0.29 | 1.40 |
| Food | 0.89 | 0.61 | 1.29 | 0.59 | -0.46 | 2.11 |
| Machinery | 0.91 | 0.73 | 1.16 | 0.56 | -0.36 | 1.81 |
| Mining | 0.71 | 0.04 | 1.85 | -1.07 | -5.83 | 7.02 |
| Motor vehicles | 0.91 | 0.73 | 1.13 | 0.65 | -0.03 | 1.49 |
| Printing | 0.94 | 0.05 | 1.63 | 0.89 | -0.71 | 2.15 |
| Pulp and paper | 0.89 | -0.16 | 1.56 | 0.45 | -4.78 | 3.80 |
| Rubber and plastic | 0.90 | 0.63 | 1.23 | 0.65 | -0.26 | 1.76 |
| Stone and mineral | 0.86 | 0.40 | 1.31 | 0.55 | -0.89 | 1.98 |
| Textile | 1.00 | 0.77 | 1.25 | 0.97 | -0.67 | 2.82 |
| Wood | 0.70 | 0.34 | 1.16 | 0.22 | -0.72 | 1.43 |

Table 5 reveals that the short-term rebound effect is on average partial in a majority of the studied sectors, ranging from 70% in *Wood* to 100% in *Textile*. These results suggest that in most sectors (except *Textile*) the energy (and emissions) savings expected from EEI were not totally offset because of the short-term rebound effect. However, given the magnitude of these numbers, we can conclude that partial rebound effect in the short run was quite substantial in Swedish manufacturing. In the long run, the energy rebound effects range from super conservation to partial rebound. Partial rebound effects were smallest in the *Chemical* sector and largest in the *Textile* sector. Super-conservation was found in *Mining*, implying that a 1% increase in EEI leads, on average, to a more

[10] For comparison, Table 5A in the Appendix shows the sector-level averages of the short- and long-term rebound effects excluding bad outputs.

than 1% reduction in energy demand. It is also notable that, in all studied sectors, the long-term rebound effect was smaller than the short-term effect, implying that within each sector, energy and emission savings due to EEI are larger in the long run compared to the short run.

Sector averages of short- and long-term rebound effects ranged from partial to super- conservation, but firm-level rebound effects varied over an even wider range. Indeed, all possible scenarios ranging from backfire to super-conservation were observed at firm-level. Therefore, policy aimed at EEI must account for this heterogeneity in some way, because the impact will vary substantially among firms and to some degree among sectors.

## 5.4 EEI Outcomes in the Swedish Manufacturing Industry

EEI potentially benefits the environment through emission savings, the industry by cost savings from re-optimization of inputs, or of course it can benefit both concerns. In this section, we conduct a post-estimation descriptive analysis to identify sectors in which EEI mainly benefited the environment or the industry.

To do this, we used the sector averages of energy efficiency scores as well as the short- and long-term rebound effects. For each sector, we also considered the yearly averages of energy use, $CO_2$ emissions and output. We also calculated the yearly averages of energy and $CO_2$ intensities, defined respectively as energy and $CO_2$ emissions per unit of output (similarly to Pardo Martínez and Silveira, 2013) during the period 1997–2008. These measures are presented in Table 6.[11] There are substantial differences among the different sectors in terms of energy efficiency scores, short- and long-term energy rebound effects, energy use, and $CO_2$ emissions and output.

Promoting EEI in *Basic iron and steel* had by far the largest environmental impact in terms of $CO_2$ emission savings both in the short run and long run. *Stone and mineral*, *Mining*, *Pulp and paper*, *Chemical* and *Food* followed *Basic iron and steel* in the short run. In the long-term, EEI in *Mining*, *Chemical*, and *Pulp and paper* resulted in the largest $CO_2$ emission savings after *Basic iron and steel*, based on $CO_2$ emissions and sector-level energy efficiency and rebound effect.

In terms of energy savings, EEI in *Pulp and paper* led to the largest energy savings in absolute terms both in the short and long run, because this sector is the most energy intensive. In the short run, *Basic iron and steel*, *Wood*, and *Mining* also had substantial energy savings from EEI. In the long run, *Basic iron and steel*, *Mining*, and *Chemical* had the largest energy savings due to EEI.

[11] Sector names are shortened in Table 6 as follwing: *Basic iron and steel* (BIS), *Chemical* (CHE), *Electro* (ELC), *Fabricated metal products* (FAB), *Food* (FOO), *Machinery* (MCH), *Mining* (MIN), *Motor vehicles* (MVH), *Printing* (PRT), *Pulp and paper* (PAP), *Rubber and plastic* (RPL), *Stone and mineral* (STM), *Textiles* (TEX), *Wood* (WOO).

This ranking is based on the energy demand in absolute terms as well as sector averages of energy efficiency and the rebound effect.

EEI reduces the real unit cost of energy service for producers and gives incentives to re-optimize such that the energy input is substituted for other inputs to the extent that it is physically possible (and economically feasible/beneficial). This reduction in the cost of energy and subsequent re-optimization could result in production being scaled up, which in turn would potentially increase emissions, and the end results would be harm to the environment. A sustainable solution suggests that EEI should be promoted in sectors where economic growth can come with the lowest environmental impact, hereafter referred to as "sustainable" output growth. Such sectors should be characterized by these conditions: (i) energy efficiency is low and hence there is enough room for EEI to have an effect; (ii) the rebound effect is high, implying that producers will have large cost savings due to re-optimization of inputs; (iii) output per unit of $CO_2$ emission is relatively high, implying that environmental effects of scaling up production are not substantial in relative terms. In Table 6, we report an index constructed on these three conditions that ranks the manufacturing sectors in terms of their potential for "sustainable" output growth (see rows "Sustainable growth in the short run" and "Sustainable growth in the long run"). The top contender for achieving "sustainable" output growth, in both in the short and long run, is *Electro*, while the next two sectors are *Machinery* and *Motor vehicles*. EEI in these sectors have the largest potential for scaling up production with minimal harm to the environment. This information is highly relevant for policy makers when they allocate resources for promoting EEI. Table 6A in Appendix presents the formulas used to calculate our indicators in Table 6.

Table 6. EEI outcomes in the Swedish manufacturing industry (including bad outputs)

| | BIS | CHE | ELC | FAB | FOO | MCH | MIN | MVH | PRT | PAP | RPL | STM | TEX | WOO |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Data and assumptions** | | | | | | | | | | | | | | |
| Energy demand (GWh/year) | 22509 | 8655 | 722 | 370 | 4968 | 1989 | 4883 | 2754 | 268 | 36700 | 928 | 4722 | 485 | 6367 |
| CO2 emissions (KTon/year) | 5606 | 865 | 34 | 24 | 623 | 106 | 608 | 189 | 21 | 1750 | 64 | 1084 | 67 | 68 |
| Energy efficiency (%) | 70 | 64 | 54 | 53 | 56 | 46 | 63 | 57 | 67 | 72 | 54 | 56 | 64 | 67 |
| Short_run rebound effect (%) | 90 | 85 | 93 | 87 | 89 | 91 | 71 | 91 | 94 | 89 | 90 | 86 | 100 | 70 |
| Long_run rebound effect (%) | 18 | 3 | 79 | 59 | 59 | 56 | -107 | 65 | 89 | 45 | 65 | 55 | 97 | 22 |
| Energy intensity (KWh/SEK) | 0.574 | 0.141 | 0.005 | 0.07 | 0.055 | 0.026 | 0.413 | 0.017 | 0.055 | 0.433 | 0.075 | 0.316 | 0.118 | 0.13 |
| CO2 intensity (Kilo/SEK) | 0.143 | 0.014 | 0 | 0.005 | 0.007 | 0.001 | 0.051 | 0.001 | 0.004 | 0.021 | 0.005 | 0.073 | 0.016 | 0.001 |
| Output (millions of unit/year) | 39205 | 61329 | 135832 | 5254 | 90127 | 76780 | 11821 | 162203 | 4862 | 84712 | 12401 | 14946 | 4127 | 48870 |
| **Expected savings** | | | | | | | | | | | | | | |
| Energy demand (GWh/year) | 6753 | 3116 | 332 | 174 | 2186 | 1074 | 1807 | 1184 | 88 | 10276 | 427 | 2078 | 175 | 2101 |
| CO2 emissions (KTon/year) | 1682 | 311 | 16 | 11 | 274 | 57 | 225 | 81 | 7 | 490 | 29 | 477 | 24 | 22 |
| **Actual savings** | | | | | | | | | | | | | | |
| Energy (short run (%)) | 3 | 5 | 3 | 6 | 5 | 5 | 11 | 4 | 2 | 3 | 5 | 6 | 0 | 10 |
| Energy (long run (%)) | 25 | 35 | 10 | 19 | 18 | 24 | 77 | 15 | 4 | 15 | 16 | 20 | 1 | 26 |
| Energy (short run (GWh/year)) | 675 | 467 | 23 | 23 | 240 | 97 | 524 | 107 | 5 | 1130 | 43 | 291 | 0 | 630 |
| Energy (long run (GWh/year)) | 5537 | 3022 | 70 | 71 | 896 | 473 | 3740 | 414 | 10 | 5652 | 149 | 935 | 5 | 1639 |
| CO2emission (short run (KTon/year)) | 168 | 47 | 1 | 1 | 30 | 5 | 65 | 7 | 0 | 54 | 3 | 67 | 0 | 7 |
| CO2 emission (long run (KTon/year)) | 1379 | 302 | 3 | 5 | 112 | 25 | 466 | 28 | 1 | 270 | 10 | 215 | 1 | 18 |
| **Effects on growth** | | | | | | | | | | | | | | |
| Output growth (short run) | 10585 | 18767 | 58109 | 2148 | 35294 | 37730 | 3105 | 63470 | 1508 | 21110 | 5134 | 5656 | 1486 | 11289 |
| Output growth (long run) | 2117 | 662 | 49361 | 1457 | 23397 | 23218 | -4680 | 45336 | 1428 | 10674 | 3708 | 3617 | 1441 | 3548 |
| Sustainable growth (short run) | 2 | 22 | 1709 | 90 | 57 | 356 | 5 | 336 | 72 | 12 | 80 | 5 | 22 | 166 |
| Sustainable growth (long run) | 0 | 1 | 1452 | 61 | 38 | 219 | -8 | 240 | 68 | 6 | 58 | 3 | 22 | 52 |
| **Rebound effects** | | | | | | | | | | | | | | |
| Energy demand offset (short run (GWh)) | 6077 | 2648 | 309 | 151 | 1945 | 977 | 1283 | 1078 | 83 | 9146 | 384 | 1787 | 175 | 1471 |
| Energy demand offset (long run (GWh)) | 1215 | 93 | 262 | 103 | 1290 | 601 | -1933 | 770 | 79 | 4624 | 277 | 1143 | 169 | 462 |
| CO2 emissions offset (short run (KTon)) | 1514 | 265 | 15 | 10 | 244 | 52 | 160 | 74 | 7 | 436 | 26 | 410 | 24 | 16 |
| CO2 emissions offset (long run (KTon)) | 303 | 9 | 12 | 7 | 162 | 32 | -241 | 53 | 6 | 221 | 19 | 262 | 23 | 5 |

# 6 Conclusions

In this study, we estimated the short- and long-term energy rebound effects for all 14 sectors in the Swedish manufacturing industry over the period 1997–2008. We applied a two-stage approach, first using DEA to calculate an energy efficiency score for each firm for each year, and then using a dynamic panel data regression model to estimate both the short- and long-term rebound effects. We also explored the effects that firm characteristics and policy related variables had on the size of rebound effects.

We found that the energy rebound effect was best described as *partial* within majority of manufacturing sectors, meaning that the rebound effect mitigated, but did not totally offset, the expected energy and emission savings from EEI. Hence, promoting EEI was beneficial from both environmental and energy saving perspectives. This result to some extent justified the restriction imposed on the range of the rebound effect in the study by Amjadi et al. (2018). It was also clear that complete realization of both short- and long-term emission and energy savings from EEI may require complementary policy actions, such as e.g. energy taxes, to correct upwards the price of energy, which would mitigate the rebound effect.

Our post-estimation analysis provides a guide to policy makers by identifying sectors where promoting EEI is more likely to have a desirable impact on the environment, energy savings and/or “sustainable” output growth. Our results suggested that different desirable outcomes can potentially be achieved by EEI in different sectors, mainly due to sector-specific characteristics such as $CO_2$ emissions, energy consumption and output per unit of emission. We found that EEI had the largest positive impact on the environment, energy saving and “sustainable” output growth in *Basic iron and steel*, *Pulp and paper* and *Electro*, in that order. These results agree with earlier findings Amjadi et al., (2018) where were also found that EEI in *Basic iron and steel* and *Pulp and paper* results in, respectively, the largest $CO_2$ emission savings and largest total energy savings in Swedish heavy industry.

Because energy demanded by Swedish manufacturing is about 45% of Sweden’s total energy use in 2008 (Statistics Sweden (SCB); cited in Martinez and Silveira, 2013), the energy rebound effects have important implications for design and implementation of energy and climate-related policies. For example, in sectors with significant rebound effects, policy aimed at EEI should be accompanied by complementary measures (such as energy taxes) to help mitigate the effects of energy becoming effectively less costly, and thus neutralize some of the unintended consequences that come with EEI.

# References

Adetutu, M. O., Glass, A. J. and Weyman-Jones, T. G. (2016) Economy-wide estimates of rebound effects: Evidence from panel data, *Energy Journal*, vol.37(3) pp. 251 – 269.

Allan, G., Hanley, N., McGregor, P., Swales, K. and Turner, K. (2007) The impact of increased efficiency in the industrial use of energy: a computable general equilibrium analysis for the United Kingdom, *Energy Economics*, vol.29 pp. 779 – 798.

Amjadi, G., Lundgren, T. and Persson, L. (2018) The rebound effect in Swedish heavy industry, *Energy Economics*, vol.71 pp. 140 – 148.

Andrews, D. W. K. and Lu, B. (2001) Consistent model and moment selection procedures for GMM estimation with application to dynamic panel data models, *Journal of Econometrics*, vol.101 pp. 123 – 164.

Arellano, M. and Bover, O. (1995) Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, vol.68 pp. 29 – 51.

Ayres, R. U. and Ayres, E. H. (2010) *Crossing the Energy Divide: Moving from Fossil Fuel Dependence to a Clean-Energy Future*, Upper Saddle River, NJ: Wharton School Publishing.

Baumgartner, T. and Midttun, A. (eds.) (1987) *The Politics of energy forecasting: a comparative study of energy forecasting in Western Europe and North America*, New York, NY: Oxford University Press.

Bentzen, J. (2004) Estimating the rebound effect in US manufacturing energy consumption, *Energy Economics*, vol.26 pp. 123 – 134.

Bergman, M. (1996) *Estimating Investment Adjustment Costs and Capital Rates from the Production Function, Umeå Economic Studies 406*, Sweden: Umeå University.

Borenstein, S. (2015) A microeconomic framework for evaluating energy efficiency rebound and some implications, *Energy Journal*, vol.36(1) pp. 1 – 21.

Broberg, T., Berg, C. and Samakovlis, E. (2015) The economy wide rebound effect from improved energy efficiency in Swedish industries – A general equilibrium analysis, *Energy Policy*, vol.83 pp. 26 – 37.

Brännlund, R. and Lundgren, T. (2010) Environmental policy and profitability – evidence from Swedish industry, *Environmental Economics and Policy Studies*, vol.12(1-2) pp. 59 – 78.

Dahlqvist, A., Lundgren, T. and Marklund, P. (2020) The rebound effect in energy-intensive industries: a factor demand model with asymmetric price response, *The Energy Journal*, vol.42(3).

Debreu, G. (1951) The Coefficient of Resource Utilization, *Econometrica*, vol.19(3) pp. 273 –292.

Färe, R. and Grosskopf, S. (1985) A Nonparametric Cost Approach to Scale Efficiency, *Scandinavian Journal of Economics*, vol.87 pp. 594 – 604.

Färe, R. and Grosskopf, S. (2004) *New Directions: Efficiency and Productivity*, New York: NY: Springer Science & Business Media, Inc.

Farrell, M. J. (1957) The measurement of productive efficiency, *Journal of the Royal Statistical Society*, vol.120 pp. 253 – 281.

Gillingham, K., Rapson, D. and Wagner, G. (2014) The rebound effect and energy efficiency policy, *Review of Environmental Economics and Policy*, vol.10(1) pp. 68 – 88.

Greening, L. A., Greene, D. L. and Difiglio, C. (2000) Energy efficiency and consumption – the rebound effect – a survey, *Energy Policy*, vol.28(6–7) pp. 389 – 401.

Grepperud, S. and Rasmussen, I. (2004) A general equilibrium assessment of rebound effects, *Energy Economics*, vol.26 pp. 261 – 82.

Hanley, N. D., McGregor, P., Swales, J. and Turner, K. (2009) Do increases in energy efficiency improve environmental quality and sustainability? *Ecological Economics*, vol.68 pp. 692 – 709.

Khazzoom, J.D., (1980) Economic implications of mandated efficiency in standards for household appliances, *Energy Journal*, vol. 1 (4) pp. 21 – 40.

King, M. A. and Fullerton, D. (1984) *The Taxation of Income from Capital*, Chicago, IL: The University of Chicago Press.

Lin, B. and Li, J. (2014) The rebound effect for heavy industry: empirical evidence from China, *Energy Policy*, vol.74 pp. 589 – 599.

Lin, B. and Xie, X. (2015) Factor substitution and rebound effect in China's food industry, *Energy Conversion and Management*, vol.105 pp. 20 – 29.

Lundgren, T. (1998) Capital Spending in the Swedish Forest Industry Sector - Four Classical Investment Models, *Journal of Forest Economics*, vol. 4(1) pp. 61 – 83.

Nadel, S. (1993) The Take-Back Effect – Fact or Fiction? [Online], Available from: *https://www.aceee.org/research-report/u933* [Accessed 2 January 2018].

Orea, L., Llorca, M. and Filippini, M. (2015) A new approach to measuring the rebound effect associated to energy efficiency improvements: an application to the US residential energy demand, *Energy Economics*, vol.49 pp. 599 – 609.

Pardo Martínez, C. I. and Silveira, S. (2013) Energy efficiency and CO2 emissions in Swedish manufacturing industries, *Energy Efficiency*, vol.6 pp. 117 – 133.

Roodman, D. (2009) How to do xtabond2: an introduction to difference and system GMM in Stata, *The Stata Journal*, vol.9(1) pp. 86 – 136.

Saunders, H. D. (1992) The Khazzoom–Brookes postulate and neoclassical growth, *Energy Journal*, vol.13(4) pp. 130 – 148.

Saunders, H. D. (2000) A view from the macro side: rebound, backfire, and Khazzoom–Brookes, *Energy Policy*, vol.28 pp. 439 – 449.

Saunders, H. D. (2008) Fuel conserving (and using) production functions, *Energy Economics*, vol.30 pp. 2184 – 2235.

Saunders, H. D. (2013) Historical evidence for energy consumption rebound in 30 US sectors and a toolkit for rebound analysts, *Technological Forecasting and Social Change*, vol.80(7) pp. 1317 – 1330.

Simar, L. and Wilson, P. W. (1998) Sensitivity analysis of efficiency scores: how to bootstrap in nonparametric frontier models, *Management Science*, vol.44(1) pp. 49 – 61.

Sorrell, S. and Dimitropoulos, J. (2008) The rebound effect: Microeconomic definitions, limitations and extensions, *Ecological Economics*, vol.65 pp. 636 – 649.

Sorrell, S., Dimitropoulos, J. and Sommerville, M. (2009) Empirical estimates of direct rebound effects: a review, *Energy Policy*, vol.37 pp. 1356 – 1371.

Stocker, T. F., Qin, D., Plattner, G., Tignor, M. M. B., Allen, S. K., Boschung, J., Nauels, A., Xia, Y., Bex, V. and Midgley, P. M. (eds.) (2013) *Climate Change 2013: The Physical Science Basis* [Online], Available from: https://www.ipcc.ch/site/assets/uploads/2018/03/WG1AR5_SummaryVolume_FINAL.pdf [Accessed 8 January 2020].

Swedish Energy Agency (2015) *Energy in Sweden 2015* [Online], Available from: https://www. energimyndigheten.se [Accessed 15 January 2018].

The Secretary - General's Advisory Group on Energy and Climate Change (AGECC) (2010) Energy for a Sustainable Future [Online], Available from: *https://www.unido.org/sites/default/files/2010-05/AGECCsummaryreport_0.pdf* [Accessed 15 September 2020].

Vikström, P. (2008) *Energy efficiency and energy demand: a historical CGE investigation on the rebound effect in the Swedish economy 1957*, Umeå Papers in Economic History, number 35.

Washida, T. (2004) Economy-wide model of rebound effect for environmental efficiency, *International Workshop on Sustainable Consumption*, Leeds: University of Leeds. Also *3rd World Congress of Environmental and Resource Economists*, Kyoto.

# Appendix

Table 3A. Average bias-corrected energy efficiency scores (excluding bad outputs)

| Sector | Average efficiency score |
|---|---|
| Mining | 0.49 |
| Stone and mineral | 0.48 |
| Textile | 0.46 |
| Printing | 0.46 |
| pulp and paper | 0.46 |
| Chemical | 0.43 |
| Motor vehicles | 0.41 |
| Wood | 0.40 |
| Rubber and plastic | 0.39 |
| Electro | 0.32 |
| Basic iron and steel | 0.30 |
| Food | 0.29 |
| Machinery | 0.26 |
| Fabricated metal products | 0.17 |

Table 4A. Parameter estimates for the dynamic energy demand model by system GMM (excluding bad outputs)

| Sector | *lag(ln(E), 1)* | *lag(ln(E), 2)* | *lnY* | *lnRPCE* | *lnRPLE* | *lnEF* | *DECSlnEF* | *EPlnEF* | *DFSlnEF* | *Hansen test* | *AR1* | *AR2* | *df* | *Firms* | *Obs.* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Basic iron and steel | 0.54* | | 0.42 | 0 | 0.28 | -0.56 | -0.09** | 0.00 | -0.02 | 1 | 0.04 | 0.57 | 71 | 55 | 381 |
| Chemical | 0.71*** | | 0.30*** | 0.15* | 0.17** | -0.15* | -0.26*** | 0.00* | -0.02 | 0.20 | 0.01 | 0.10 | 65 | 167 | 1110 |
| Electro | 0.63*** | | 0.33*** | -0.09 | 0.27*** | -0.24*** | -0.30*** | 0.00** | 0.00 | 0.41 | 0.00 | 0.12 | 71 | 197 | 976 |
| Fabricated metal products | 0.72*** | | 0.21*** | 0.38** | -0.06 | -0.02 | -0.15*** | 0.00 | -0.02* | 0.14 | 0.00 | 0.53 | 71 | 387 | 1736 |
| Food | 0.63*** | | 0.33*** | 0.21*** | 0.19*** | -0.22*** | -0.19*** | 0.00 | -0.02 | 0.13 | 0.00 | 0.49 | 71 | 375 | 2223 |
| Machinery | 0.66*** | | 0.32*** | 0.02 | 0.17*** | -0.32*** | -0.18*** | 0.00*** | -0.02 | 0.31 | 0.00 | 0.16 | 71 | 571 | 3054 |
| Mining | 0.77*** | | 0.24 | -0.16 | 0.44 | 0.06 | -0.35** | 0.00 | 0.07 | 1 | 0.03 | 0.51 | 71 | 43 | 245 |
| Motor vehicles | 0.49*** | 0.18*** | 0.30*** | 0.12 | 0.09 | -0.21** | -0.21*** | 0.00 | -0.05** | 0.43 | 0.00 | 0.13 | 69 | 185 | 1097 |
| Printing | 0.44*** | | 0.57*** | 0.48 | -0.08 | -0.14 | -0.51*** | 0.00 | -0.05 | 0.99 | 0.02 | 0.69 | 71 | 140 | 633 |
| Pulp and paper | 0.60*** | | 0.41*** | 0.10 | 0.52*** | -0.14 | -0.61*** | 0.00 | 0.03 | 0.37 | 0.00 | 0.74 | 71 | 126 | 966 |
| Rubber and plastic | 0.73*** | | 0.27*** | 0.23** | 0.15** | -0.09 | -0.19*** | 0.00 | 0.01 | 0.35 | 0.01 | 0.47 | 71 | 216 | 1176 |
| Stone and mineral | 0.61*** | | 0.35*** | 0.35* | 0.48*** | 0.22 | -0.42*** | 0.00* | -0.08 | 0.36 | 0.10 | 0.25 | 68 | 154 | 933 |
| Textile | 0.81*** | | 0.20*** | 0.31*** | 0.14 | 0.03 | -0.22*** | 0.00 | 0.04 | 0.48 | 0.00 | 0.49 | 71 | 119 | 643 |
| Wood | 0.50*** | | 0.48*** | 0.40** | 0.15 | -0.20*** | -0.35*** | 0.00 | -0.02 | 0.11 | 0.00 | 0.97 | 71 | 292 | 1435 |

***, **, and * indicate 1%, 5% and 10% significance levels, respectively.

Table 5A. Sector-level averages of the short- and the long-run rebound effects (excluding bad outputs)

| Sector | Short-run Rebound Effect | Long-run Rebound Effect |
|---|---|---|
| Basic iron and steel | 0.51 | -0.06 |
| Chemical | 0.61 | -0.36 |
| Electro | 0.72 | 0.23 |
| Fabricated metal products | 0.90 | 0.64 |
| Food | 0.65 | 0.06 |
| Machinery | 0.66 | 0.01 |
| Mining | 0.81 | 0.14 |
| Motor vehicles | 0.76 | 0.28 |
| Printing | 0.60 | 0.29 |
| Pulp and paper | 0.46 | -0.35 |
| Rubber and plastic | 0.76 | 0.10 |
| Stone and mineral | 0.71 | 0.25 |
| Textile | 0.84 | 0.16 |
| Wood | 0.57 | 0.14 |

These results were obtained using a DEA framework excluding bad outputs. Table 5.A shows that the average of the short-term rebound effect was partial in all 14 sectors, and ranged from 46% in *Pulp and paper* to 90% in *Fabricated metal products*. This implies that the energy and emission savings expected from EEI were not totally offset by the short-term rebound effect, though the size of rebound effect was significant. In the long run, rebound effect was partial in most of the studied sectors. However, our results indicate a super-conservation response to EEI in the three of energy-intensive sectors *Pulp and paper*, *Basic iron and steel* and *Chemical*, implying that a 1% EEI led on average to a >1% reduction in energy demand. These have important policy implications for promoting EEI in the long run, because these three sectors constituted about three-quarters of total energy use in Swedish manufacturing (Swedish Energy Agency report, 2015). Table 5.A also shows that the long-term rebound effect was smaller than the short-term rebound effect, implying that in the long run, energy and emission savings induced by EEI are larger than the short run. Although sector averages of the short- and long-term rebound effects range from partial to super-conservation, firm-level rebound effects included all possible rebound effects, i.e., from backfire to super-conservation.

Table 6A. Formulas used to calculate EEI outcomes in the Swedish manufacturing industry (reported in Table 6)

| |
|---|
| Actual energy saving (%)=(((1-(0,01× rebound effect (%)))×(100-Energy efficiency(%)) )/(100)×100) |
| Actual energy saving (GWh/year)=((Actual energy saving (%))/100)×Energy demand(GWh/year) |
| Actual $CO_2$ emission saving (KTon/year)=((Actual energy saving (%))/100)×$CO_2$ emission (KTon/year) |
| Actual output growth=((100-Energy efficiency (%)))/100×(rebound effect(%))/(100×Output(millions of unit)) |
| Actual sustainable growth= Actual output growth/($CO_2$ emission (KTon/year)) |