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CERE Working Paper, 2017:1

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Abstract

Energy efficiency improvement (EEI) benefits the climate and matters for energy security. The potential emission and energy savings due to EEI may however not fully materialize due to the rebound effect. In this study, we measure the size of rebound effect for the two energy types fuel and electricity within the four most energy intensive sectors in Sweden – pulp and paper, basic iron and steel, chemical, and mining. We use a detailed firm-level panel data set for the period 2000-2008 and apply Stochastic Frontier Analysis (SFA) for measuring the rebound effect. We find that both fuel and electricity rebound effects do not fully offset the potential for energy and emission savings. Furthermore, we find CO_2 intensity and fuel and electricity share as the two main determinants of rebound effect in Swedish heavy industry. Our results seems to imply that it matters both to what extent and where to promote EEI, as the rebound effect varies between sectors as well as between firms within sectors.

Keywords: Energy efficiency improvement; Rebound effect; Stochastic Frontier Analysis.

[1] This research was funded by the Swedish Energy Agency.

1. Introduction

For the last decades climate change and energy issues have been high on the political agenda in many countries. The European Commission set a framework[2] for 2030 with focus on energy efficiency improvement[3] (EEI) to reduce greenhouse gas (GHG) emissions and improve energy security. While EEI is often claimed to be the most cost-effective tool to achieve these objectives (see e.g., Gillingham et al., 2009; Visa, 2014), its effect on final energy use, and thereby also on GHG emissions, remains debatable. The basic argument is that EEI reduces the real unit price of energy service, which potentially gives rise to both substitution and income effects. Both of these effects can lower, or even offset, the potential full energy- and emission savings based on engineering type of calculations. This is known as the rebound or take-back effect.

The concept of the rebound effect is generally associated with behavioral responses to new technology. Within energy economics, the concept of rebound effect is traced back to the British economist, William Stanley Jevons (1865), who noticed that improving the energy efficiency of the steam engine increased the industrial use of coal in production since it becomes more cost-efficient. This phenomenon is known as the "Jevons paradox". From a welfare economics point of view, the rebound effect should be thought of as economically beneficial since it is mainly a re-optimization response to changes in price and income, which creates economic value and enhances the level of welfare (Borenstein, 2015). That said, the magnitude of the rebound effect should be taken into account while evaluating the effectiveness of energy efficiency policies addressing climate change and energy demand.

There is both theoretical and empirical evidence on the existence of a rebound effect (e.g., Bentzen, 2004; Saunders, 2008; Sorrell et al. 2009; Saunders, 2013; Orea et al., 2015). The empirical estimates of the rebound effect varies widely and are not always comparable across studies, mainly due to the lack of uniform definitions of the rebound effect, different types of methodologies, energy services, countries, and levels of data aggregation (Gillingham et al., 2014; Orea et al., 2015). The majority of studies estimate consumer-related rebound effects

[2] The European Commission target for 2030 is to reduce GHG emissions by 40 percent compared to 1990 level and increasing the energy efficiency by 27 percent.
[3] Using less energy to provide the same service or providing more services with the same energy (e.g. Ansuategi et al., 2014).

while the producer-side rebound effect has not been sufficiently paid attention to. The knowledge about the size of producer-related rebound effect is however an important matter since the industrial energy use constitutes a significant part of total energy use. For example, the industrial energy use in Sweden in 2013 adds up to about 40 percent of total end-use energy (Swedish Energy Agency, 2015). Hence, further research on producer-side rebound effect is deeply needed. In this study, we aim to fill part of this gap by estimating the firm-level rebound effect for four energy intensive sectors in Sweden. We follow Saunders (2008) definition of producer rebound effect and estimate the direct rebound effect as the take-back percentage of expected energy savings due to a decrease in the real unit price of energy service following EEI. For the estimation we apply a methodology proposed by Orea et al. (2015), which integrates the measurement of the rebound effect into a stochastic energy demand frontier analysis.

This paper contributes to the rebound effect literature in several ways. First, we estimate the production-side rebound effect related to electricity- and fuel use, which has not yet received sufficient attention in the literature. Second, we use a detailed firm-level dataset for Swedish firms within four energy-intensive sectors – basic iron and steel, chemical, pulp and paper, and mining, which to the best of our knowledge has not been done using Swedish data. There are industrial energy efficiency related studies on Swedish industry data such as Thollander and Dotzauer (2010), Thollander et al. (2012). They do however not focus specifically on the rebound effect. Third, we apply the Orea et al. (2015) approach to the production-side of the economy to obtain a direct measure of the producer-side rebound effect. This approach integrates the measurement of the rebound effect into a stochastic energy demand frontier model and is capable of measuring the energy efficiency and rebound effect simultaneously. Fourth, since our approach measures the rebound effect through its determinants, we can identify significant determinants for the rebound effect in four Swedish energy intensive sectors.

This paper is organized as follows. Section 2 briefly reviews the concept of the rebound effect as well as theoretical and empirical studies on the topic. Section 3 provides the theoretical framework on which our study is based. Section 4 describes the data, while section 5 presents results and provides an illustration of the implication of our result. Finally, section 6 provides a discussion and conclusions.

2. Literature and background

More than a century after the Jevons' paradox, Khazzoom (1980) introduced the concept to the economic literature as the "direct rebound effect". The mechanism behind the rebound effect can be explained as when energy efficiency improves, the real per unit price of energy service drops, since the energy required producing that service decreases. This lead to both micro- and macro-level behavioral changes in the energy use. Although the basic intuition would be that EEI reduces the use of energy, the price drop potentially gives rise to opposite effects and a relative increase in energy use. The final change in energy use may actually be such that the total use of energy increases more than without the EEI (Saunders, 1992). This is known as backfire, which seems to result in an outcome opposite to the initial objectives of EEI policies. The rebound effect may occur on the consumer side, as well as on the producer side of the economy. The focus in this paper is producer side, firm level, rebound effects.

Production-side rebound effects

Production-side rebound effects come from producers' behavioral responses to EEI once the real unit price of energy service[4] drops due to less energy required to produce one unit of output. The range of these responses can be divided into three main categories: (1) a direct rebound effect, (2) an indirect or secondary use rebound effect, and (3) an economy-wide effect (Greening et al., 2000). The direct effect relates to the fact that a firm re-optimize the use of inputs when the price of one input (energy) changes. A relatively lower price on energy would, in general, lead to an increased demand for that input. The extent of the direct response may potentially vary depending on the type of energy, timing, firm/production type etc. (Sorrell et al., 2009). The indirect rebound effect arises from scaling up the production. In a competitive market, a reduced price on inputs would lead to a reduced price of output, which would increase the demand and final consumption of the output. Both the direct and indirect responses result from the combination of income and substitution effects (Chitnis et al., 2013). Finally, the economy-wide effect may arise due to the large direct and indirect responses, which change the input demand, output supply and equilibrium prices in other markets. New products and

[4] Economists define energy services as useful work (Ayres and Ayres, 2010). Alternatively, it 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).

industries may arise, leading to a further increase in energy use. The sum of all these effects may increase the total energy demand in the production process more than without the EEI (Saunders, 1992). Hence, following any EEI, the potential of energy savings will depend on all above-mentioned responses which gives rise to different magnitudes of the rebound effect: (1) super conservation (negative rebound effect, implying higher savings than expected), (2) zero-rebound (actual energy savings are equal to potential savings), (3) partial rebound (actual energy savings are less than potential savings, (4) full rebound (no energy savings), and (5) backfire (negative energy savings) (e.g., Greening et al., 2000).

Theoretical aspects of the producer-side rebound effect

After Khazzoom (1980), Saunders (1992) for the first time theorized the production-side rebound effect. Given particular assumptions, he applied the neoclassical growth theory and showed that the Jevons' Paradox is possible since backfire would be a likely outcome of EEI in the production side of the economy.[5] The driving forces for the production-side rebound effect were later explained as a composition of two effects. First, the EEI increases productivity of energy, which decreases the unit cost of energy service and therefore makes energy more attractive as an input. This leads to substitution of energy input for other inputs. Second, EEI increases the production possibilities through cost savings, which lead to scaling up the output level and therefore increased energy consumption (e.g., Saunders, 1992; Saunders, 2008). The size of the production-side rebound effect, however, depends on the elasticities of substitution and productivity gains (Greening et al., 2000). Later, Saunders (2008) contributed to the theoretical literature on production-side rebound effect by formally naming the two above-mentioned forces as the "intensity" and "output/income" effects, respectively.

Empirical literature on the producer-side rebound effect

Regarding the empirical estimates of the rebound effect, an extensive empirical literature has evolved since Khazzoom (1980). The most obvious estimate of the rebound effect would be obtained from the elasticity of demand for energy services with respect to changes in energy efficiency (Orea et al., 2015). However, due to lack of, or inaccurate data on, the energy services

[5] Saunders (1992) suggests that the efficiency improvement of any production factor increases the energy use more than without such improvement.

and energy efficiency (Sorrell et al., 2009; Orea et al., 2015), other elasticities have been used as indirect measures of the rebound effect (Sorrell and Dimitropoulos, 2008).

Regarding the number of studies measuring the *consumer-side* rebound effects and *producer-side* rebound effects, there is a huge difference. For the consumer-related rebound effects, a great deal of work has been done measuring the rebound effects for different sources of energy demand such as e.g. personal automobile transport, heating and space cooling. However, much remains to be done on the producer-side rebound effect (Greening et al., 2000). Nadel (1993) reviews most of the earlier rebound effect studies for industrial sectors and concludes that on average there is a very small rebound effect, about 2 percent, due to increased production levels resulted from efficiency improvements. More recent studies such as Bentzen (2004) and Saunders (2013) perform estimates for the producer-side rebound effect in the U.S. Bentzen (2004) estimates the direct rebound effect in the US manufacturing sector by applying a time series data for the period of 1949-1999. The energy-price elasticity is considered as a measure of the size of rebound effect and estimated by a system of factor demand equations. An upper bound of 24 percent for the direct rebound effect is found. Saunders (2013) measures the size of rebound effect as the elasticity of substitution between energy and other production factors. Saunders provides estimates of both the short- and long-run sector-specific direct rebound effect for 30 U.S. sectors, as well as aggregated estimates of direct rebound effect for period 1960-2005. He considers different efficiency scenarios, where efficiency improvement is assumed for energy or for all production factors. He simulates the rebound effects assuming that no EEI has occurred after 1980, and finds average size of rebound effects for different sectors of about 125 and 60 percent for the short-run (1981-1990) and the long-run (1991-2000), respectively. The estimates of short-run sector-specific rebound effects for paper and chemical and mining, with only EEI, are most relevant for us. However due to different dataset and methodologies, the findings are not fully comparable.

Except the studies on U.S. data, there are some studies on Chinese data. For example, Lin and Xie (2015) study the effects of EEI on China’s food industry by estimating a system of cost share equations. They estimate the direct rebound effect by examining the substitution between different inputs and conclude a direct rebound effect of about 34 percent. Lin and Li (2014) estimate the direct rebound effect for Chinese heavy industry by applying translog cost share equations. Their results show a rebound effect of about 74 percent, implying that a substantial share of potential energy savings would be offset due to a rebound effect. To meet any energy saving objectives for China, they suggest implementing energy price reforms and energy taxes.

There are also studies measuring the size of economy-wide production-side rebound effect such as Grepperud and Rasmussen (2004), Washida (2004), Allan et al. (2007), Vikström (2008), Hanley et al. (2009), Broberg et al. (2015). These studies apply computable general equilibrium (CGE) models assuming different percentage of EEI and calculate different sizes of rebound effect ranging from partial rebound to back fire. In general, the CGE approach measures the economy-wide effects as a sum of direct and indirect effects and not necessarily the effect on stimulating new products and markets.

To conclude, previous studies report a wide range of estimates for the producer-related rebound effect, ranging from very small partial rebound effects to backfire. However, the empirical estimates of the size of rebound effect are widely spread and are not always comparable across different studies. This is not only due to the different elasticities applied, but also due to the lack of uniform definitions of the rebound effect, types of energy services, countries and levels of data aggregation (Gillingham et al., 2014; Orea et al., 2015).

3. Methodology

In theory, the rebound effect could, and should, be directly obtained from the elasticity of demand for energy services with respect to changes in energy efficiency (Orea et al., 2015). However due to the lack of data on energy services and/or energy efficiency, the rebound effect has often been indirectly measured through different elasticities as proxies – such as the own-price elasticity of the demand for energy (Sorell, 2009; Orea et al., 2015). In this paper, we apply an approach proposed by Orea et al. (2015) that provides a direct measure of the rebound effect. The approach integrates the measurement of the rebound effect into a stochastic energy demand frontier model and is capable of measuring the energy efficiency and rebound effect simultaneously. In this study, we modify their model to be better suited for measuring the producer-side rebound effect.

The advantage of the SFA approach, relative to the previously applied econometric methods, is that it can be considered as a direct measure of the rebound effect (Orea et al, 2015). Sorrell et al. (2009) point at sources of bias (overestimation) due to potentially incorrect assumptions when applying elasticities as proxies for the size of rebound effect. They argue that using such proxies implies two assumptions. First, the changes in energy demand due to EEI is equal but opposite in sign to that due to change in energy prices. Second, that EEI is exogenous. These assumptions are unlikely to hold, in particular since EEI gains are in general achieved through investments. Moreover, they argue that the response to price increases tends to be higher than the response to price drops (note that this asymmetry was addressed by Bentzen, 2004). Since many studies include periods of rising energy prices in their elasticity estimates, they tend to overestimate the responses to falling energy prices (Sorrell et al., 2009). These issues tend to overestimate of the size of rebound effect when elasticities are applied as proxies.

The energy demand of a firm depends on its levels of production, energy efficiency and its behavioral response to EEI (size of the rebound effect). This implies that there is an identification problem between the energy efficiency and the rebound effect, where price elasticities as proxies to measure the rebound effect fail to account for all these factors simultaneously. More specifically, such approaches implicitly assume that all firms are fully efficient which bias the rebound effect estimates. Also, studies using elasticities to proxy the rebound effect are simulating, not estimating, the true rebound effect; the procedure entails estimating the elasticity and then simulating an efficiency improvement that, in effect, makes energy cheaper by lowering the effective price of energy. The SFA technique, however, involves directly estimating the rebound effect based on actual energy efficiency changes.

The stochastic energy demand frontier

For a cost-minimizing firm, a stochastic energy demand frontier shows the minimum level of energy required to produce any level of output, given the technology and other inputs available. That said, in a setup with labor, capital and energy as inputs, the standard stochastic energy demand frontier model shows inefficiency in use of energy as positive deviations from the frontier. The frontier approach identifies both the efficient and inefficient firms. The energy efficient firms are located on (or close to) the frontier using the minimum requirement of energy to produce the chosen level of output. The inefficient firms are however not located on (or close to) the frontier. Instead, for any energy inefficient firm, the difference between the observed energy demand and the optimal energy demand shows the overall inefficiency as a combination of the technical inefficiency (the failure to operate at the production function) and the allocative inefficiency (the failure to minimize production costs) (Filippini and Hunt, 2012). Following Filippini and Hunt (2011, 2012), while adopting a different set of variables to fit their model for producers, the stochastic energy demand frontier can be written as

$$\ln E = \ln f(\mathbf{X},\boldsymbol{\beta}) + v + u \tag{1}$$

E is the actual energy demand by each producer as a function of a vector of variables, $\mathbf{X}$, such as level of output, energy prices and other inputs, and $\boldsymbol{\beta}$ is a vector of coefficients to be estimated. In addition, the energy demand is not fully deterministic, which is captured by the error terms v and u. v is the conventional symmetric random noise and is assumed to be normally distributed, i.e., $v \sim N(0,\sigma_v^2)$, and u is a one-sided error term capturing the level of underlying energy inefficiency and is assumed to be distributed half normal, i.e. $u \sim N^+(\mu,\sigma_u^2)$. u can vary across producers and over time. The identification of these error terms is dependent on the one sided distribution of u. If a firm is fully energy efficient, $f(\mathbf{X},\boldsymbol{\beta})$ corresponds to its demand for energy. But if the producer is not on the frontier, u measures the distance between the producer's observed and the optimal energy use, i.e. energy inefficiency. The energy efficiency score (EE) is then calculated given the estimated energy inefficiency as:

$$EE = \exp(-u) \tag{2}$$

This measure of energy efficiency takes a value between zero and one, where one indicates a fully efficient producer, i.e., when $u = 0$.

Measuring the rebound effect in the stochastic energy demand frontier

There are different mathematical definitions of the rebound effect. In this paper, we follow the definition proposed by Saunders (2008) where the rebound, R, is defined as:

$$R = 1 + \varepsilon_{EE}^{E}, \tag{3}$$

where ε_{EE}^{E} is referred to as the elasticity of demand for energy use with respect to changes in energy efficiency. ε_{EE}^{E} can be shown as:

$$\varepsilon_{EE}^{E}=\frac{d\ln E}{d\ln EE} \tag{4}$$

Therefore, R measures the percentage rebound such that, for instance, if the energy use is reduced by half of the EEI, rebound is 0.5 (50 percent) and if the energy use remains unchanged following the EEI, rebound is 1 (100 percent). Replacing the denominator in equation (4) by equation (2) gives that

$$\varepsilon_{EE}^{E}=\frac{d\ln E}{d\ln EE}=\frac{d\ln E}{d\ln\exp(-u)}=-\frac{d\ln E}{du} \tag{5}$$

The rebound effect in equation (3) can potentially take different values corresponding to 5 different scenarios of energy conservation following EEI: backfire $(R>1)$, full rebound effect $(R=1)$, partial rebound effect $(R<1)$, zero rebound effect $(R=0)$, and super-conservation $(R<0)$. Equation (3) implies that the rebound effect can be measured by applying any energy demand frontier model including an inefficiency term (Orea et al., 2015). However, Orea et al. (2015) point out that ε_{EE}^{E} in the standard stochastic energy demand frontier presented by equation (1) is equal to minus one. Therefore, the standard stochastic energy demand frontier imposes a zero rebound effect which contradicts many of empirical findings summarized in section 2.

The stochastic energy demand frontier with non-zero rebound effects

Orea et al. (2015) reason on the empirical findings that the rebound effect may increase, decrease or even fully offset the potential energy savings of EEI on actual energy demand. They, therefore, modify the standard stochastic energy demand model by adding the rebound as a correction factor $(1-R)$ which interacts with energy inefficiency term u.[6] This can be defined as:

$$\ln E=\ln f\left(\mathbf{X},\boldsymbol{\beta}\right)+v+\left(1-R\right)u, \tag{6}$$

[6] A similar specification to the equation (6) can be found in the efficiency literature such as Kumbhakar (1990), where a non-stochastic function as scaling function is introduced as a part of inefficiency term u. In the application of SFA in measuring the rebound effect, as discussed in Orea et al. (2015), the R in the correction factor $(1-R)$ captures the rebound effect.

where $u = -\ln EE \geq 0$. In this framework the changes in energy demand is not necessarily proportional to EEI (reduction in u). However, Orea et al. (2015) note that the underlying energy efficiency in equation (6) can only be identified if the rebound effect is not full, otherwise the identification of v and u would not be possible due to a symmetric error term. In equation (6), the error components v and u have the same distributions as before, i.e., $v \sim N(0, \sigma_v^2)$ and $u \sim N^+(\mu, \sigma_u^2)$. The changes in energy demand do not necessarily follow a one-to-one relation with changes in energy efficiency. Both R and energy inefficiency level are unobservable since they are related to demand for energy services which is, again, unobservable (Orea et al., 2015). To estimate equation (6), Orea et al. (2015) define R as a set of determinants of the demand for energy services, which allows for identifying the impact of different factors on the size of the rebound effect. Replacing the rebound effect variable in equation (6) by a rebound effect function, we have:

$$\ln E = \ln f\left(\mathbf{X}, \boldsymbol{\beta}\right) + v + \left[1 - R\left(\boldsymbol{\lambda}'\mathbf{Z}\right)\right]u \tag{7}$$

This equation is estimated by a maximum likelihood estimator (MLE) where the vector of variables, $\mathbf{Z}$, determines the rebound effect.[7] Regarding the choice of rebound effect functional form, Sounders (2008) argues for the Gallant and Fourier functions which are the most flexible as they allow for the potential range of rebound effect. Orea et al. (2015), however, remark some methodological and practical limitations in using these forms in their framework. In the maximum likelihood approach, the value $\left[1 - R\left(\boldsymbol{\lambda}'\mathbf{Z}\right)\right]$ is required to be positive to be able to decompose the overall error term into inefficiency and noise. Therefore, $R\left(\boldsymbol{\lambda}'\mathbf{Z}\right)$ should be smaller than one, implying that estimating the full rebound and backfire is not possible in this setting. This is not necessarily too problematic since there is very little empirical evidence on rebound effects equal or larger than one. Orea et al. (2015) suggest two functional forms for the rebound effects

$$R(\mathbf{Z}, \boldsymbol{\lambda}) = \frac{\exp(\boldsymbol{\lambda}'\mathbf{Z})}{1 + \exp(\boldsymbol{\lambda}'\mathbf{Z})} \tag{8}$$

[7] For estimating this model, we apply the general scaling property framework which has been discussed in different models such as Kumbhakar (1990) and Lee and Schmidt (1993).

$$R(\mathbf{Z},\boldsymbol{\lambda})=\frac{\exp(\boldsymbol{\lambda}'\mathbf{Z})-1}{\exp(\boldsymbol{\lambda}'\mathbf{Z})} \tag{9}$$

The functional form in equation (8) allows for partial rebound effects, while equation (9) captures both the partial and super-conservation effects. In the present study, the super-conservation response to EEI is highly counter-intuitive and the rebound function is therefore defined by equation (8). That said, any rebound effect in the present study refers to a "partial" rebound effect.[8]

As pointed out by Orea et al. (2015), the $\boldsymbol{\lambda}'\mathbf{Z}$ function can be estimated with or without an intercept. However, in the former case the estimated intercept is biased and should be adjusted.

Empirical specification

In this paper, we aim to estimate the size of direct rebound effects for fuel and electricity demand separately in the Swedish heavy industry. We follow the methodological framework of Lundgren et al. (2016) for a stochastic input demand frontier. In this framework a four-factor stochastic production technology is assumed for each of four Swedish energy intensive sectors. The final good in each sector is produced using the inputs labor, capital, electricity and fuel, adopting the cost minimizing behavior given a particular output level. The stochastic electricity and fuel demand frontier, then, is specified while assuming that the production technology of each sector has only two substitutable inputs in the short-run: electricity and fuel. Labor and capital are assumed to be quasi-fixed factors. A quasi-fixed capital stock is uncontroversial in the short run and the assumption of quasi-fixed labor follows Lundgren et al. (2016) and Lundgren and Marklund (2015).[9] As inefficiency level and rebound effect affect the energy demand of each firm, it is added to the model. Finally, our short-run stochastic energy demand frontier for energy type i and firm x in period t can be specified as

$$\begin{aligned}\ln E_i^{xt} &= \beta_{i,0}+\beta_{i,1}\ln Y^{xt}+\beta_2\ln\left(p_j/p_i\right)^{xt}+\beta_{i,3}\ln L^{xt}+\beta_{i,4}\ln K^{xt}+\beta_{i,5}Yd^{xt}\\ &\quad+\left[1-R\left(\boldsymbol{\lambda}'\mathbf{Z}\right)\right]u_{xt}+v_{xt}\quad ,\end{aligned} \tag{10}$$

[8] Results from specifying the rebound function as equation (9) are presented in the Appendix B.

[9] Given the Swedish labor market and the Swedish law, treating sector specific labor as fixed is reasonable in the short run.

Where i and j represent the two energy types, i.e., fuel and electricity. β's are parameters to be estimated. Y denotes quantity of output produced, while p is the price of either electricity or fuel. K and L are capital and labor, which are assumed to be quasi-fixed. Therefore, our results capture the short run efficiency and the direct rebound effect.[10] Yd is year dummies. The overall error term is composed of a white noise term $v \sim N(0,\sigma_v^2)$ and an energy inefficiency term $u \sim N^+(\mu,\sigma_u^2)$.

Our specified fuel and electricity stochastic demand frontier models are in the spirit of the cost-minimizing factor demand equations derived in Schmidt and Lovell (1979) and discussed further in Kumbhakar and Lovell (2000). However, our energy inefficiency measure includes both technical and allocative inefficiency, as in Filippini and Hunt (2011), and our energy demand frontier model includes an extra rebound term which interacts with inefficiency term.

Turning to the explicit rebound effect function, it potentially allows for including different economic and policy variables as determinants of rebound effect. Considering limitations of our data as well as our mission to capture determinants of producer rebound effect, we include three groups of variables: (1) output level and energy type relative prices to capture income and substitution effects, (2) firm-specific characteristics such as CO_2 intensity and fuel and electricity share to capture the effects of environmental performance and technology, and (3) a dummy variable for firms participating in the European Emission Trade System (EU-ETS). Furthermore, it is interesting to show whether the rebound effect changes over time. However, inclusion of year dummies in the rebound function like in the frontier would require many parameters to be estimated. To avoid this, we included time trend and time trend squared in the rebound function to give this function more flexibility[11]. The $\boldsymbol{\lambda}'\mathbf{Z}$ function can be written for energy type i and firm x in period t as

$$\begin{aligned}\lambda' Z_i^{xt} &= \lambda_1 \ln Y^{xt} + \lambda_2 \ln\left(p_j/p_i\right)^{xt} + \lambda_3 \ln\left(CO_2/Y\right)^{xt} + \lambda_4 \ln energytype^i - share^{xt} \\ &\quad + \lambda_5 dETS^{xt} + \lambda_6 timetrend + \lambda_7 (timetrend)^2\end{aligned} \tag{11}$$

[10] If labor and capital are not quasi fixed, i.e., their relative price to energy is included in the frontier instead of capital stock and labor force, then the estimate of rebound effect reflects both the direct and indirect rebound effect since we allow the substitution between energy and other inputs.

[11] We have estimated models with year dummies both in the frontier and rebound function. The rebound specification including time trend and time trend squared produces the most reasonable result.

Like equation (10), Y and p denotes quantity of produced output and price, respectively. The ratio CO_2/Y denotes CO_2 intensity defined as the CO_2 emission per unit of output. The variable $energytype^i - share$ denotes the fuel, or electricity, share and is defined as the ratio of fuel or electricity to the total sum of fuel and electricity used. The participation in EU-ETS is included as a dummy variable. This dummy takes the value zero for all firms before 2005, and one for firms participating in the EU-ETS in the period 2005 to 2008.

Regarding the estimation of our model there are some points worth mentioning. First, equation (10) is estimated simultaneously with the rebound function, equation (8), using a MLE. Second, no intercept is included in equation (11), since our one-sided error term is $\left[1-R\left(\lambda'Z\right)\right]u$ and the estimates of σ_u and the intercept cannot be separated using the MLE.[12] Based on the result and discussion of Orea et al. (2015), including no intercept in the $\boldsymbol{\lambda}'\mathbf{Z}$ function implies that we estimate an upper bound for efficiency scores and a lower bound for rebound effect.

4. Data

We apply a detailed firm-level unbalanced panel data on the four Swedish energy intensive sectors: basic iron and steel, pulp and paper, chemical and mining. The dataset is provided by Statistics Sweden and has been used in papers such as Brännlund et al. (2015), Lundgren and Marklund (2015) and Lundgren et al. (2016). Our study covers the period 2000-2008. The four sectors we analyze consume about 75 percent of end-use energy in Swedish industry in 2010 and are referred to as heavy industries (Thollander et al., 2013). Descriptive statistics of the variables are presented in Table 1. All variables with monetary values are defined in year 2008 prices.

[12] Orea et al. (2015) also discuss this issue.

Table 1. Firm level descriptive - yearly averages for 2000-2008

	Iron and steel	Pulp and paper	Chemical	Mining
Output (index)	1124	957	593	457
	(2127)	(1602)	(2392)	(1433)
Capital (MSEK)	755	759	500	744
	(1644)	(1385)	(2261)	(2344)
Labor	510	370	261	238
	(849)	(540)	(928)	(655)
Fuel (GWh)	504	176	35	78
	(1824)	(344)	(115)	(271)
Fuel price (SEK/kWh)	0.61	0.37	0.57	0.81
	(0.25)	(0.25)	(1.07)	(0.3)
Electricity (GWh)	164	256	46	117
	(337)	(587)	(157)	(385)
Electricity price (SEK/kWh)	0.57	0.40	0.54	0.75
	(0.16)	(0.18)	(0.33)	(0.32)
CO_2 (Ton)	169	19	8	24
	(632)	(35)	(30)	(84)
No. of observations	335	815	978	234

Standard deviations within brackets

Output is calculated as the firm's final sales divided by its corresponding producer price index for a given sector. Capital stock, as explained in Lundgren et al. (2016), is calculated using gross investment data and the perpetual inventory method. Labor is the number of employees. Fuel is an aggregate of coal, oil, gaseous fuel, biofuel and other fuels. Fuel and electricity prices are calculated as the ratio of the fuel/electricity costs to quantity used. The data we use also contains information on carbon emissions (ton).

5. Results and analysis

Our results indicate a significant rebound effect in all four studied sectors for both fuel and electricity. In this section, we first present the estimates of the fuel and electricity rebound effects and efficiency levels. Later, the parameter estimates for the stochastic fuel and electricity demand frontier model are shown, followed by a numerical example to illustrate the impact of the rebound effect estimates on fuel and electricity consumption and CO_2 emissions.

5.1. Fuel rebound effect and fuel efficiency

The estimated sizes of the fuel rebound effect and fuel efficiency are presented in table 2 and 3, respectively.[13] The results indicate that the average rebound effects for fuel range between 31 percent in the pulp and paper sector to 54 percent in the iron and steel sector. The standard deviation of the fuel rebound effect is highest in the mining sector, indicating that this sector is the most heterogeneous in terms of behavioral response to fuel efficiency improvements.

Table 2. Fuel rebound – summary statistics

	Obs.	**Mean.**	**Std. Dev.**	**Min**	**Max**
Iron and Steel	327	0.54	0.12	0.33	0.90
Chemical	957	0.42	0.13	0.14	0.96
Pulp and Paper	804	0.31	0.12	0.15	0.83
Mining	219	0.50	0.19	0.14	0.95

Regarding the values of the fuel efficiency, the estimates indicate that the average fuel efficiency ranges between 81 percent in the mining sector to 98 percent in the pulp and paper sector. This implies that the performance of firms on average in the pulp and paper sector is closer to the best-practice frontier. The standard deviation of the fuel efficiency is highest in the mining sector, indicating that firms in this sector are the most heterogeneous in terms of fuel efficiency.

Table 3. Fuel efficiency – summary statistics

	Obs.	**Mean.**	**Std. Dev.**
Iron and Steel	327	0.94	0.14
Chemical	957	0.97	0.09
Pulp and Paper	804	0.98	0.06
Mining	219	0.81	0.29

[13] Equivalent tables with a rebound effect function presented in equation (9), i.e., super-conservation, are presented in the Appendix B, tables 2 and 3. As it is shown, this specification of rebound function also yields estimates for fuel rebound effects within the range of partial effects for all the studied sectors.

5.2. Electricity rebound effect and electricity efficiency

The estimated sizes of the electricity rebound effect and electricity efficiency are presented in table 4 and 5, respectively.[14] The estimates in table 4 show that the average electricity rebound effect ranges between 26 percent for pulp and paper and 79 percent for iron and steel sector. Like the fuel rebound size, the standard deviation of the electricity rebound effect is highest in the mining sector, indicating that this sector is the most heterogeneous in terms of behavioral response to electricity efficiency improvement.

Table 4. Electricity rebound – summary statistics

	Obs.	**Mean.**	**Std. Dev.**	**Min**	**Max**
Iron and Steel	327	0.79	0.08	0.48	0.94
Chemical	957	0.75	0.07	0.34	0.94
Pulp and Paper	804	0.26	0.15	0.01	0.94
Mining	219	0.37	0.16	0.10	0.98

Regarding the values of the electricity efficiency, the estimates indicate that the average electricity efficiency ranges between 49 percent in both the iron and steel and the chemical sectors to 85 percent in the mining sector. The standard deviation of the electricity efficiency is highest in the chemical sector, indicating that firms in this sector are the most heterogeneous in terms of electricity efficiency.

Table 5. Electricity efficiency – summary statistics

	Obs.	**Mean.**	**Std. Dev.**
Iron and Steel	327	0.49	0.28
Chemical	957	0.49	0.30
Pulp and Paper	804	0.83	0.21
Mining	219	0.85	0.24

[14] Equivalent tables with a rebound effect function presented in equation (9), i.e., super-conservation, are presented in the Appendix B, tables 5 and 6. As it is shown, this specification of rebound function also yields estimates for electricity rebound effects within the range of partial effects for all the studied sectors.

Both the rebound and efficiency statistics may potentially vary over time. However when looking into these estimates over the time period, no obvious trends are found from the year 2000 to 2008.

5.3. Parameter estimates for the stochastic fuel demand frontier and the fuel rebound function

Given the estimated average rebound effects in the previous sections, it is interesting to further investigate potential underlying factors and mechanisms. As presented in section 4, the specification of the rebound function potentially captures effects related to output level, energy-type relative prices, CO_2 intensity, fuel and electricity share, EU-ETS, and time period. Tables 6 and 7 present the parameter estimates for the stochastic fuel and electricity demand frontiers and rebound functions, respectively.

Regarding the stochastic fuel demand frontier for all sectors, the statistically significant parameter estimates all have the expected signs.[15] Both the dependent and independent variables are in logarithmic form, meaning that the estimated coefficients can be interpreted as elasticities. For all four sectors, wherever the estimates are significant, the results suggest that the fuel demand is inelastic ($\varepsilon < 1$) with respect to output, labor, capital and the relative price of electricity to fuel. Given at least some significant parameter estimates for the time dummies, the fuel demand frontier is affected by time in all sectors except mining. The significant estimates of the variance parameters σ_u and σ_v indicate that fuel inefficiency indeed exists and the estimates are, in that respect, valid.

Regarding the coefficient estimates in the fuel rebound function; the CO_2 intensity and fuel share show statistically significant negative effects on the size of rebound effect in all four sectors. These results suggest that the fuel rebound effects within each sector are lower among firms with a more CO_2 intensive production and/or a higher fuel share, showing that these firms have more to gain from fuel conservation when fuel efficiency improves.

[15] Statistically significant is, in this section, defined as significant at 5% level.

Table 6. Parameter estimates for the stochastic fuel demand frontier model

	Variable	Basic Iron&Steel	Pulp&Paper	Chemical	Mining
Frontier					
	$\ln Y$	0.178	0.205*	-0.103	0.440*
	$\ln (p_e/p_f)$	0.193	0.363*	0.228*	-0.315
	$\ln L$	0.278*	0.288*	0.355*	0.383*
	$\ln K$	0.217*	0.119*	-0.027	0.052
	$\text{Yd} - 2001$	-0.075	-0.134	0.522*	0.076
	$\text{Yd} - 2002$	-0.102	-0.294*	0.930*	0.203
	$\text{Yd} - 2003$	-0.069	-0.397*	1.177*	0.216
	$\text{Yd} - 2004$	0.037	-0.493*	1.170*	0.086
	$\text{Yd} - 2005$	0.146	-0.519*	1.015*	0.067
	$\text{Yd} - 2006$	0.282	-0.574*	0.719*	0.116
	$\text{Yd} - 2007$	0.473*	-0.543*	0.195	-0.016
	$\text{Yd} - 2008$	0.666*	-0.511*	-0.354	-0.194
	_cons	0.297	0.023	0.106	0.130
Error component					
	$\sigma_u$constant	4.898*	4.392*	4.802*	4.280*
	$\sigma_v$constant	-3.838*	-2.908*	-2.695*	-3.091*
Rebound effect					
	$\ln Y$	-0.036	-0.143*	-0.202*	-0.005
	$\ln (p_e/p_f)$	0.072	0.099	0.081	-0.131
	$\ln (CO_2/Y)$	-0.078*	-0.111*	-0.136*	-0.274*
	$\ln fuel\ share$	-0.429*	-0.376*	-0.284*	-0.382*
	dETS	-0.022	0.003	-0.036	0.028
	timetrend	-0.035	-0.102*	0.321*	0.089
	$(\text{timetrend})^2$	0.007*	0.007	-0.034*	-0.010

* 5% significance level.

p_e/p_f is the relative price of electricity to fuel.

The output level has a negative impact on the fuel rebound effect for pulp and paper, and chemical. This implies that the fuel rebound effects are statistically lower among firms with higher output level in the pulp and paper and chemical sectors. Neither the relative price of electricity to fuel nor the EU-ETS membership dummy show any statistically significant effects on the size of fuel rebound in any of the sectors. Finally, for all included sectors except mining, the rebound function is changing over time.

5.4. Parameter estimates for the stochastic electricity demand frontier and the electricity rebound function

Regarding the stochastic electricity demand frontier for all sectors, the statistically significant parameter estimates have signs consistent with the expectations. As in the previous section, the parameter estimates in table 7 can be interpreted as elasticities. For all four sectors, wherever the estimates are significant, the results suggest that electricity demand is inelastic ($\varepsilon < 1$) with respect to output, labor, capital and the relative price of fuel to electricity. In all the included sectors, the frontier changes over time (at least one time dummy is significant). The estimates of the variance parameters σ_u and σ_v indicate that electricity inefficiency indeed exists and the estimates are, in that respect, valid.

Regarding the coefficient estimates in the electricity rebound function; the CO_2 intensity and electricity share show statistically significant negative effects on the size of rebound effect in all four sectors. These results suggest that the electricity rebound effect within each sector is lower among firms with a more CO_2 intensive production and/or a higher share of electricity in their total energy use. This suggests that these firms have more to gain from electricity conservation following an electricity efficiency improvement.

Table 7. Parameter estimates for the stochastic electricity demand frontier model

	Variable	*Basic Iron&Steel*	*Pulp&Paper*	*Chemical*	*Mining*
Frontier					
	$\ln Y$	0.631*	0.211*	0.697*	0.233*
	$\ln (p_f/p_e)$	0.056	0.242*	0.275*	0.056
	$\ln L$	0.387*	0.417*	0.315*	0.354*
	$\ln K$	0.158*	0.211*	0.149*	-0.146
	$\mathrm{Yd} - 2001$	0.029	0.020	0.103	-0.111
	$\mathrm{Yd} - 2002$	0.058	-0.043	0.155*	-0.123
	$\mathrm{Yd} - 2003$	0.092	-0.073	0.249*	-0.313
	$\mathrm{Yd} - 2004$	0.174*	-0.112	0.226*	-0.547*
	$\mathrm{Yd} - 2005$	0.230*	-0.068	0.253*	-0.609*
	$\mathrm{Yd} - 2006$	0.284*	-0.146	0.267*	-0.696*
	$\mathrm{Yd} - 2007$	0.390*	-0.144	0.235*	-0.843*
	$\mathrm{Yd} - 2008$	0.455*	-0.210*	0.264*	-0.884*
	_cons	1.205*	2.576*	0.823*	3.102*
Error component					
	$\sigma_u$constant	4.902*	2.810*	4.408*	3.574*
	$\sigma_v$constant	-4.044*	-2.902*	-2.283*	-2.836*
Rebound effect					
	$\ln Y$	0.221*	-0.239*	0.155*	-0.093*
	$\ln (p_f/p_e)$	0.012	0.560*	0.172*	0.021
	$\ln (CO_2/Y)$	-0.153*	-0.169*	-0.149*	-0.203*
	$\ln \mathit{elctricityshare}$	-0.572*	-1.203*	-0.599*	-0.911*
	dETS	-0.033	0.112	-0.088*	0.067
	timetrend	-0.007	0.025	0.054*	-0.087
	$(\mathrm{timetrend})^2$	0.004	-0.009	-0.004	-0.002

* 5% siginificance level.
p_f/p_e is the relative price of fuel to electricity.

Moreover, the results indicate that the electricity rebound effects are statistically higher among firms with higher output level in the basic iron and steel and chemical sectors, and among firms with lower output level in the pulp and paper and mining sectors. The relative price of fuel to electricity shows statistically significant positive effect on the size of rebound effect in the pulp and paper and chemical sectors. The EU-ETS membership dummy indicates a statistically significant and negative effect on the size of rebound effect in the chemical sector. Finally, the rebound function is changing over time only for the chemical sector.

5.5. Differentiating policy with consideration to the level of rebound effect

Given the results, it is safe to claim that the CO_2 intensity and fuel, or electricity share, are the most statistically significant determinants of the rebound effect in the Swedish heavy industry. It is interesting from a policy perspective to explore how these two variables vary with the size of the fuel and electricity rebound effects. Therefore, a descriptive analysis based on the rebound estimates has been done to shed light on how policy-makers may identify and target firms with different sizes of rebound effect. The results are shown in tables 1-8 in the Appendix A. For each of the different sectors, the estimated fuel and electricity rebound effects of each firm in each year are grouped into quartiles of firms. The average of rebound effects, CO_2 intensity and fuel, or electricity, share are calculated for each quartile group. For both fuel and electricity rebound, the tables show significant variation among the average rebound effects in all the quartile groups, implying heterogeneity in responses to EEI within each sector. For the fuel rebound, both the average of CO_2 intensity and fuel share per quartile group follow negatively the average size of fuel rebound effect. However for the electricity rebound, the quartile groups of CO_2 intensity follow the average electricity rebound size negatively while the electricity share pattern is less conclusive. For the other three sectors, our analysis shows that the average electricity share follows the average electricity rebound size negatively while the CO_2 intensity pattern is less conclusive.

The policy implication is that for the fuel rebound effect, both CO_2 intensity and fuel share can be used to effectively target firms with lower fuel rebound effect within each sector. For the electricity rebound effect in the pulp and paper sector, the CO_2 intensity is the best indicator to identify the firms with lower rebound effect, while the electricity share is best indicator to effectively target the firms with lower electricity rebound effect.

5.6. Impacts of the rebound effects on energy demand and GHG emissions in the studied sectors

Although the analysis of table 6 and 7 gives valuable insights, it is also interesting to translate the results to more policy relevant indicators. So, in this subsection we evaluate the impacts of the estimated rebound effect on sector specific fuel and electricity demand, and CO_2 emissions, based on a hypothetical 20 percent EEI scenario. The 20 percent scenario is highly relevant given the EU target of 20 percent EEI by the year 2020. The calculation is based on our estimated average rebound effects, yearly average fuel and electricity use and yearly average CO_2 emission levels for each sector during the period 2000-2008. The impact of the rebound effect is calculated as the difference between potential (no rebound) and actual outcomes (including rebound).

Table 8. The effects from a 20% energy efficiency improvement

	Iron and Steel	Pulp and Paper	Chemical	Mining
Data and assumptions				
Fuel demand (GWh)	18760	15938	3803	2028
Electricity demand (GWh)	6104	23182	4999	3042
CO_2 emissions (ton)	6275	1709	845	625
EEI scenario (%)	20.0	20.0	20.0	20.0
Fuel rebound effect (%)	54	31	42	50
Electricity rebound effect (%)	79	26	75	37
Potential reductions				
Fuel demand (GWh)	3752	3188	761	406
Electricity demand (GWh)	1221	4636	1000	608
CO_2 emissions (ton)	1255	342	169	125
Actual reductions				
Actual fuel saving (%)	9.2	13.8	11.6	10.0
Actual electricity saving (%)	4.2	14.8	5.0	12.6
Actual fuel saving	1726	2199	441	203
Actual electricity saving	256	3431	250	383
Actual CO_2 emission saving	577	236	98	62
Rebound effect impacts				
Fuel demand offset	2026	988	319	203
Electricity demand offset	965	1205	750	225
CO_2 emissions offset	678	106	71	62

As shown in table 8, the largest fuel rebound effect is found in the iron and steel sector which also has the highest fuel demand and CO_2 emissions, with about four times more CO_2 emissions than the most energy intensive pulp and paper sector. Controlling for rebound effect, our finding in table 8 implies that the actual CO_2 emission saving is largest in basic iron and steel sector due to its high demand of fuel with a relatively large share of brown fuel. On the other hand, the largest saving in fuel demand is found in the pulp and paper sector which also has by far the largest saving in electricity demand. As shown in the table, pulp and paper sector is the most energy intensive sector with a higher share of electricity in total energy demand and a relatively more green composition of fuel. This explains why basic iron and steel stands for the most of CO_2 emission although pulp and paper is the most energy intensive sector.

6. Discussion and Conclusions

In this study, we have shown the existence of partial rebound effects in all four energy intensive sectors of the Swedish heavy industry. Since the potential energy and emission savings are not totally offset by rebound effects, promoting EEI can still be justified from both environmental and energy security points of view. This however requires evaluation against other alternatives to ensure that the most cost effective tool is chosen to reach environmental and energy security targets. Policy makers should also consider that the full energy and emission saving potentials of an EEI will not be reached unless complementary policy actions, e.g., taxes or quotas, are taken to offset the rebound effect.

Our results highlight important implications regarding both environmental and energy security related policies. From an environmental policy perspective, our result suggests that the iron and steel sector becomes particularly important for policy makers to consider for promoting EEI. The CO_2 emission saving from an EEI is more than twice as large in the iron and steel sector than in the pulp and paper sector, and larger than the other three energy intensive sectors together. From an energy security point of view, our results suggest that the pulp and paper sector, the most energy intensive sector, matters the most (particularly regarding electricity). In the pulp and paper sector, the electricity savings due to EEI are more than ten times larger than in the basic iron and steel sector, and almost four times larger than in the other three energy intensive sectors together.

The two key determinants for the size of the rebound effect found in our study are the level of CO_2 intensity, the fuel share and the electricity share. These variables have a negative effect on the size of the rebound effect in all studied sectors and for both energy types. This suggests that within each sector, the rebound effect is lower among the relatively more polluting firms and the firms using relatively more of the energy type which has experienced efficiency gains. Descriptive analysis of the rebound estimates also confirms that the rebound effect varies with the level of CO_2 intensity and energy share for each sector. For the fuel rebound, this result has important policy implications as it suggests that policies promoting fuel efficiency to address CO_2 emissions, or energy security, will be more effective among the relatively more polluting firms. For the electricity rebound, the results suggest that policies promoting electricity efficiency to reduce electricity demand will be more effective among the more polluting firms in the pulp and paper sector, as well as among firms with a higher electricity share in the three other sectors included in this study. Hence, given limited resources for promoting EEI, the optimal allocation of such resources would be among the worst polluters within each sector rather than equally distributed.

To conclude, the existence of energy rebound effects in the Swedish energy-intensive industries has important economic and environmental implications. EEI can potentially benefit the environment and improve energy security due to reduced levels of energy consumption, as well as the industries due to cost savings for any given level of production. The existence of a rebound effect also implies that industries can benefit by re-optimizing their choices of inputs and increasing their output level. Where the rebound effect is high, EEI will to a larger extent benefit the industry compared to the environment, and vice versa. Depending on the relative importance of environment, energy security and economic growth, policy makers should choose not only to what extent, but also where to promote EEI, as the rebound effect varies between sectors as well as between firms within sectors.

As for further research, it would be interesting to analyze all 14 manufacturing sectors in the Swedish industry and relate their rebound effect sizes to their potential for EEI. Given that kind of knowledge, policy makers would potentially be able to identify sectors where promotion of EEI would be most effective, i.e. the sectors with high potential for EEI but a low rebound effect.

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Appendix A

Average firm level fuel rebound sizes grouped by quartiles of rebound sizes

Table 1. Basic iron and steel sector

Quartile group of rebound	CO_2 intensity	Fuel share	Rebound size
q1	130	65%	43%
q2	13	44%	51%
q3	4	26%	60%
q4	3	8%	74%

Table 2. Pulp and paper sector

Quartile group of rebound	CO_2 intensity	Fuel share	Rebound size
q1	33	52%	21%
q2	17	49%	27%
q3	8	44%	34%
q4	2	22%	48%

Table 3. Chemical sector

Quartile group of rebound	CO_2 intensity	Fuel share	Rebound size
q1	38	64%	30%
q2	15	56%	39%
q3	4	38%	48%
q4	6	15%	62%

Table 4. Mining sector

Quartile group of rebound	CO_2 intensity	Fuel share	Rebound size
q1	153	75%	26%
q2	35	60%	38%
q3	8	35%	54%
q4	2	14%	74%

Average firm level electricity rebound sizes grouped by quartiles of rebound sizes

Table 5. Basic iron and steel sector

Quartile group of rebound	CO_2 intensity	Electricity share	Rebound size
q1	24	74%	65%
q2	35	69%	76%
q3	13	68%	80%
q4	80	46%	87%

Table 6. Pulp and paper sector

Quartile group of rebound	CO_2 intensity	Electricity share	Rebound size
q1	25	62%	11%
q2	20	57%	24%
q3	8	63%	35%
q4	6	51%	50%

Table 7. Chemical sector

Quartile group of rebound	CO_2 intensity	Electricity share	Rebound size
q1	13	75%	62%
q2	19	57%	71%
q3	18	48%	76%
q4	12	47%	83%

Table 8. Mining sector

Quartile group of rebound	CO_2 intensity	Electricity share	Rebound size
q1	16	78%	24%
q2	13	72%	35%
q3	55	46%	44%
q4	115	22%	62%

Appendix B

Table 1. Parameter estimates for fuel demand stochastic frontier model (super-conservation)

	Variable	*Basic Iron&Steel*	*Pulp&Paper*	*Chemical*	*Mining*
Frontier					
	$\ln Y$	0.832*	1.151*	-0.515*	0.076
	$\ln (p_e/p_f)$	-0.072	0.204*	0.447*	-0.272*
	$\ln L$	0.283*	0.270*	0.360*	0.395*
	$\ln K$	0.102*	0.103*	0.008	0.084
	$\mathrm{Yd}-2001$	-0.028	-0.082	-0.032	-0.159
	$\mathrm{Yd}-2002$	-0.033	-0.183	-0.023	-0.162
	$\mathrm{Yd}-2003$	-0.007	-0.241*	-0.017	-0.195
	$\mathrm{Yd}-2004$	0.046	-0.283*	-0.132	-0.334
	$\mathrm{Yd}-2005$	0.083	-0.229	-0.204	-0.366*
	$\mathrm{Yd}-2006$	0.105	-0.223	-0.303*	-0.240
	$\mathrm{Yd}-2007$	0.188	-0.118	-0.471*	-0.246
	$\mathrm{Yd}-2008$	0.243	-0.014	-0.594*	-0.328
	_cons	-2.209*	-5.045*	1.549*	1.790*
Error component					
	$\sigma_u$constant	4.983*	5.321*	2.687*	1.267*
	$\sigma_v$constant	-3.854*	-2.923*	-2.696*	-3.084*
Rebound effect					
	$\ln Y$	0.124*	0.131*	-0.129*	-0.126*
	$\ln (p_e/p_f)$	-0.006	0.014	0.058*	-0.026
	$\ln (CO_2/Y)$	-0.044*	-0.023*	-0.052*	-0.169*
	$\ln \mathit{fuel\ share}$	-0.276*	-0.181*	-0.095*	-0.221*
	dETS	-0.009	-0.007	-0.004	0.014
	timetrend	-0.006	-0.021	0.002	-0.026
	$\mathrm{timetrend}^2$	0.001	0.002	-0.001	0.002

* 5% significance level.

p_e/p_f is the relative price of electricity to fuel.

Table 2. Summary statistics of fuel rebound sizes (super-conservation)

	Obs.	Mean.	Std. Dev.	Min	Max
Iron and Steel	327	0.71	0.07	0.53	0.89
Chemical	957	0.35	0.06	0.21	0.61
Pulp and Paper	804	0.70	0.06	0.55	0.86
Mining	219	0.35	0.13	0.14	0.76

Table 3. Summary statistics of the fuel efficiency (super-conservation)

	Obs.	Mean.	Std. Dev.	Median
Iron and Steel	327	0.91	0.14	0.97
Chemical	957	0.99	0.03	0.99
Pulp and Paper	804	0.98	0.04	0.99
Mining	219	0.87	0.21	0.96

Table 4. Parameter estimates for electricity demand stochastic frontier model (super-conservation)

	Variable	*Basic Iron&Steel*	*Pulp&Paper*	*Chemical*	*Mining*
Frontier					
	$\ln Y$	0.596*	1.238*	0.738*	0.276*
	$\ln (p_f/p_e)$	0.044	0.006	0.213*	0.140
	$\ln L$	0.395*	0.247*	0.289*	0.260
	$\ln K$	0.130*	0.218*	0.139*	-0.178*
	$\mathrm{Yd} - 2001$	0.026	-0.031	0.087	-0.096
	$\mathrm{Yd} - 2002$	0.050	-0.145*	0.130	-0.044
	$\mathrm{Yd} - 2003$	0.077	-0.206*	0.210*	-0.152
	$\mathrm{Yd} - 2004$	0.154*	-0.268*	0.185*	-0.363*
	$\mathrm{Yd} - 2005$	0.203*	-0.241*	0.215*	-0.279
	$\mathrm{Yd} - 2006$	0.245*	-0.303*	0.238*	-0.285
	$\mathrm{Yd} - 2007$	0.340*	-0.283*	0.214*	-0.383*
	$\mathrm{Yd} - 2008$	0.393*	-0.276*	0.259*	-0.344
	_cons	1.349*	-1.834*	0.764*	3.271*
Error component					
	$\sigma_u$constant	3.600*	5.451*	3.220*	2.294*
	$\sigma_v$constant	-4.103*	-2.861*	-2.324*	-2.715*
Rebound effect					
	$\ln Y$	0.143*	0.300*	0.116*	-0.058*
	$\ln (p_f/p_e)$	0.003	0.029	0.091*	0.023
	$\ln (CO_2/Y)$	-0.108*	-0.046*	-0.123*	-0.075*
	$\ln electricityshare$	-0.429*	-0.336*	-0.478*	-0.474*
	dETS	-0.018	0.015	-0.053	0.044*
	$timetrend$	-0.006	-0.028	0.027	-0.016
	$(timetrend)^2$	0.002	0.001	-0.002	0.000

* 5% significance level.

p_f/p_e is the relative price of fuel to electricity.

Table 5. Summary statistics of electricity rebound sizes (super-conservation)

	Obs.	**Mean.**	**Std. Dev.**	**Min**	**Max**
Iron and Steel	327	0.71	0.07	0.48	0.88
Chemical	957	0.69	0.06	0.36	0.89
Pulp and Paper	804	0.83	0.07	0.61	0.93
Mining	219	0.48	0.09	0.33	0.90

Table 6. Summary statistics of the electricity efficiency (super-conservation)

	Obs.	**Mean.**	**Std. Dev.**	**Median**
Iron and Steel	327	0.64	0.23	0.64
Chemical	957	0.55	0.28	0.58
Pulp and Paper	804	0.56	0.30	0.62
Mining	219	0.83	0.24	0.93