DOCTORAL THESIS

Essays on Energy Efficiency, Environmental Regulation and Labor Demand in Swedish Industry

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To my parents Farah and Hadi

Abstract

Paper [I] 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 the rebound effect for 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 2000–2008 and apply a stochastic frontier analysis (SFA) for measuring the rebound effect. We find that neither fuel nor electricity rebound effects fully offset the potential energy and emission savings. Among the determinants, we find the CO_2 intensity and the fuel/electricity shares to be useful indicators for identifying firms with higher or lower rebound effects within each sector.

Paper [II] 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 emissions and energy 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.

Paper [III] Energy inefficiency in production implies that the same level of goods and services could be produced using less energy. The potential energy inefficiency of a firm may be linked to long-term structural rigidities in the production process and/or systematic shortcomings in management (persistent inefficiency), or associated with temporary issues like misallocation of resources (transient inefficiency). Eliminating or mitigating different inefficiencies may require different policy measures. Studies measuring industrial energy inefficiency have mostly focused on overall inefficiencies and have paid little attention to distinctions between the types. The aim of this study was to assess whether energy inefficiency is *transient and/or persistent* in the Swedish manufacturing industry. I used a firm-level panel dataset covering fourteen

industrial sectors from 1997–2008 and estimated a stochastic energy demand frontier model. The model included a four-component error term separating persistent and transient inefficiency from unobserved heterogeneity and random noise. I found that both transient and persistent energy inefficiencies exist in most sectors of the Swedish manufacturing industry. Overall, persistent energy inefficiency was larger than transient, but varied considerably in different manufacturing sectors. The results suggest that, generally, energy inefficiencies in the Swedish manufacturing industry were related to structural rigidities connected to technology and/or management practices.

Paper [IV] The aim of this paper was to investigate whether the environment and employment compete with each other in Swedish manufacturing industry. The effect of a marginal increase in environmental expenditure and environmental investment costs on sector-level demand for labor (employment) was studied using a detailed firm-level panel dataset for the period 2001–2008. The results showed that the sign and magnitude of the net employment effects ultimately depend on the aggregate sector-level output demand elasticity. If the output demand is inelastic, these costs induce small net improvements in employment, while a more elastic output demand suggests negative, but in most sectors relatively small, net effects on demand for labor. Hence, the results did not generally indicate a substantial trade-off between jobs and the environment. The general policy recommendation that can be drawn from this study is that, in the absence of empirically estimated output demand elasticities, a careful attitude regarding national environmental initiatives for sectors exposed to world market competition should be adopted.

Keywords: *Energy efficiency improvement, rebound effect, stochastic frontier analysis, data envelopment analysis, stochastic energy demand frontier model, persistent and transient energy inefficiency, energy inefficiency, environmental expenditure and environmental investment costs, output demand elasticity.*

Acknowledgments

When starting this journey my primary goal was to better understand economics. Little did I know how my perspective would change. I admit that I learned more about economics, but much more about myself, my potential and limits. It has been a process. But now after ALL, I feel privileged to be able to say "*I have been there and done that*".

I would like to thank my supervisors and co-authors: Lars Persson, Tommy Lundgren and Wenchao Zhou. I could not have done this without each of you. Your constructive comments and workable solutions were invaluable. My approach to research has immeasurably improved through your influence (each in different ways). I also would like to thank you for your attitude and patience in listening to my academic and non-academic matters. I hope we continue working together for years to come.

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Golnaz
Luxembourg, 23 October 2020

Contents

This PhD thesis consists of an introductory part and the following four self-contained papers:

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1 Introduction

In recent years, global concerns have been raised regarding climate change, resource scarcity, and sustainability. Generally, the production-side of the economy contributes significantly to these matters. For instance, industry was responsible for more than 30% of total global greenhouse gas (GHG) emissions in 2010 (Fischedick et al., 2014), and 36% of total energy consumption worldwide in 2014 (United States Energy Information Administration, 2017). To address the problems of GHG emissions and climate change, global and national energy targets have been set by entities like the United Nations, which in a recent report demanded action to reduce global energy intensity by 40% by 2030 (AGECC, 2010). Energy intensity is generally defined as energy use per unit of an activity like output. Energy efficiency improvement (EEI) can contribute to changes in energy intensity because such improvements imply that the same level of goods and services can be obtained using less energy.

In many ways, Sweden is a front-runner in these matters, with its ambitious climate and energy targets. Among the International Energy Agency (IEA) member states, Sweden has the lowest share of fossil fuels in its energy supply, and the second lowest carbon emission per Gross Domestic Product (GDP) and per capita (IEA, 2020). In terms of energy policy, Sweden has focused on generating a sustainable energy system, reducing energy intensity, promoting EEI, and converting from fossil fuel to renewable energy sources. For instance, Sweden aims to reduce energy intensity by 50% by the year 2030 relative to 2005 (Government offices of Sweden, 2018) and also to reach 100% renewable electricity production by 2040. In addition, Sweden has set a goal of net zero GHG emissions by 2045. In terms of energy policies, it also aims to ensure a secure energy supply at internationally competitive prices.

In the area of regulating environmental abatement activities, Sweden launched its first Environmental Protection Act in 1969 under which the State received a significant role in the protection of the environment, and the Swedish National Licensing Board was subsequently established to give permission for activities resulting in large negative environmental impacts, such as industrial activities (Swedish Environmental Protection Agency, SEPA, report 2017).

The Swedish manufacturing industry is one of the major drivers for GDP growth and employment (The Swedish Trade and Invest Council, 2016). This industry contributes about 35% of Sweden's total production value and about 20% of total employment at the national level. In 2008, there were more than 61,000 manufacturing firms in Sweden, which were responsible for about 45% of the total final energy use (Statistics Sweden (SCB); cited in Martínez and Silveira, 2013). Hence, understanding the effects that policies such as EEI and environmental regulations have on industrial energy and labor use is crucial. The industrial response to energy and environmental policies will have major implications for reaching national energy and environmental targets. Indeed, shedding light on such impacts provide guidelines in order to set more realistic and relevant policy targets.

This thesis consists of four empirical papers that analyze the effects of EEI and environmental regulations on industrial sector-level demands for energy and labor. In these papers, the relationships between major policy objectives in Sweden (such as EEI, preservation of the environment/climate, and employment) are explored to better understand how industrial firms react to these policies, and how those reactions in turn affect how and whether policy goals are met. The empirical analyses in this thesis are applied to detailed firm-level datasets for the Swedish manufacturing industry spanning the period 1997–2008.

The main research questions addressed in this thesis are: (i) What potential is there for the industrial firm to accomplish EEI both in the short run and long run?; (ii) Are there behavioral responses by firms to EEI that counteract the expected energy and emission savings?; (iii) Does a marginal change in the environmental management cost (EMC) affect sector-level employment?

Papers [I] and [II] measure firms' behavioral responses to EEI (called *energy rebound effects*) and also relative firm-level energy efficiency scores. EEI reduces the real unit price of energy services and changes the relative price of energy input in relation to other inputs. Producers respond to this change and substitute energy input for other inputs, which is referred to as the *intensity effect*. Furthermore, cost savings from the substitution can be used to increase the output level, which is referred to as *scale/output effect*. These two effects may change the expected outcome of energy policies, and together they create the *energy rebound effect*. Broadly speaking, society benefits when firms re-optimize their choice of inputs due to a change in relative input prices, but individual re-allocations may increase, decrease, or even offset the expected energy and emission savings from EEI. Papers [I] and [II] aim to measure the size of rebound effect using different approaches.

In Paper [I], we use stochastic frontier analysis (SFA) to estimate the potentials for industrial fuel and electricity efficiency improvements and also the firms' behavioral responses to such improvements, i.e. fuel and electricity rebound effects, all in one step. We perform our analysis on the four most energy-intensive sectors in Swedish industry for the period 2000–2008. The sectors are *Pulp and paper*, *Basic iron and steel*, *Chemical*, and *Mining*. In Paper [II], we adopt a two-step approach where first we calculate the potentials for EEI using data envelopment analysis (DEA) and then estimate the short- and long-term energy rebound effects using a dynamic panel data regression model. In paper [II], we expand our analysis to all 14 sectors included in the Swedish manufacturing industry for the period 1997–2008. In Papers [I] and [II], we also identify both determinants of the rebound effect, as well as sectors in which EEI either mainly benefit environmental due to energy and emission savings or mainly promote economic growth due to cost savings from efficiency gains. Our results help to set realistic energy and climate targets and to design policy mandates that show an awareness of responses to EEI.

Paper [III] estimates the overall energy efficiency for all 14 sectors in the Swedish manufacturing industry. The main purpose of this paper is to investigate whether the energy inefficiency is persistent (which would mean that the inefficiency is associated with rigidities in a firm's production process and/or systematic shortcomings in management) or whether it is transient (which would mean that inefficiency is linked to temporary shortcomings such as misallocation of resources).

In Paper [IV], focus turns to labor rather than energy use, and I estimate the effects of a marginal increase in environmental expenditures and investment costs on sector-level employment (or labor demand). This paper addresses the potential trade-off between the environment and jobs within the Swedish manufacturing industry.

2 Methodology

Papers [I–III] use efficiency and productivity analyses, while Paper [IV] uses a more conventional econometric approach. This section first introduces and reviews the concepts of efficiency and efficiency measurement, and then turns to energy efficiency in particular, and its measurement through what is called *frontier analysis*.

2.1 Efficiency

"Control is a double-edged sword; it involves both doing things right (efficiency) and doing the right thing (effectiveness). It is better to do the right thing wrong than the wrong thing right. Unfortunately, the righter we do the wrong things, the wronger we become" (Russell L. Ackoff, 1999, p. 123)

Efficiency, at its core, is a relative concept that changes over time. For instance, seen from the production side of an economy, the quality and quantity of outputs obtained from a given bundle of inputs will change over time due to technological advances. The general definition of efficiency is the use of the least amount of resources to produce the most outputs or services. This definition allows us to evaluate the performance of units like firms without considering the preferences of those firms.

2.1.1 Efficiency Measurement

There are different ways to evaluate efficiency. For instance, one might be interested in comparing the efficiency of a firm to the efficiencies of other firms within each year, or in comparing a firm's relative efficiency over time. Either way, the comparison should be conducted relative to a benchmark that represents the best practices and performances given the available technology. This boundary of the feasible technology set is called the *frontier*.

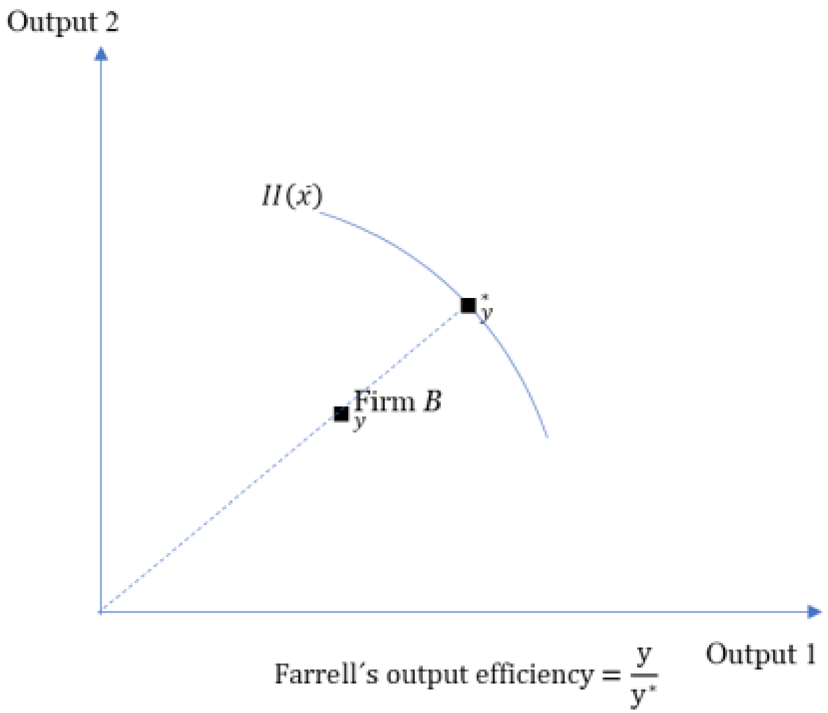
In economics, the efficiency measures proposed by Farrell (1957) are the cornerstone of modern frontier literature, which include stochastic frontier analysis (SFA) and data envelopment analysis (DEA). Farrell's efficiency measures are based on the proportional expansion of all outputs using the same bundle of inputs, which is called *output–based Farrell efficiency*, or on the proportional contraction of all inputs holding output constant, which is called *input–based Farrell efficiency*.

The *output–based Farrell efficiency* measure for a two-outputs production technology is presented in Figure 1. The output frontier (the curve labelled *II*) is the boundary of the output set and shows the maximum feasible output combinations that could be produced using a given bundle of inputs ($\bar{x}$). Firm *B* uses those inputs to produce the output combination presented at point

y. Firm *B* is inefficient because it could increase the output level from y to y^*(a point on the *II* curve) using the same bundle of inputs ($\bar{x}$). The *output–based Farrell efficiency* measure corresponds to movement along the dashed line in Figure 1, where each movement away from the origin implies proportional expansion of both outputs. With the Farrell efficiency measure (or score), a firm's inefficiency increases with the potential for output expansion.

Efficiency scores usually vary between zero and one, where lower scores indicate lower efficiency and therefore more room for efficiency improvement. In the following section, I provide a brief introduction to measuring efficiency for the input energy.

Figure 1. Farrell output-based efficiency measure

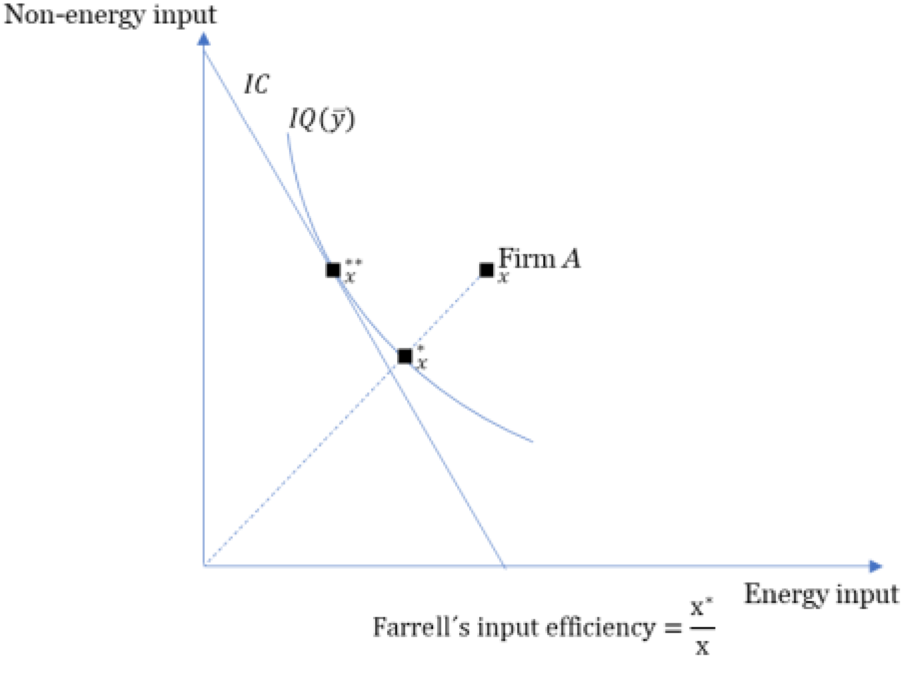


2.1.2 Energy Efficiency Measurement

Energy is of course an essential input in production. Energy efficiency is defined as the ratio of the minimum possible energy use and the observed energy use for a given level of output. Energy efficiency improves if the same level of goods and services are produced using less energy, or if more of goods and services are produced using the same amount of energy.

A Farrell-type of energy efficiency measure for a two-input production technology is presented in Figure 2, where firm *A* utilizes energy and non-energy inputs to produce a given level of output ($\bar{y}$). The graph shows the isoquant (*IQ*), interpreted as the minimum required combination of inputs to produce output level $\bar{y}$. The *IQ* curve serves as a benchmark that represents firms that are fully technically efficient in their use of inputs. *Technical efficiency* indicates the extent to which a production unit (firm) efficiently uses different inputs (e.g. labor, capital, energy) to produce output. For instance, firm *A* with the observed input combination x and output level $\bar{y}$ is technically inefficient because it would be possible to proportionally reduce all its inputs from x to x^* and still produce the output level ($\bar{y}$). The *input–based Farrell efficiency* measure corresponds to movement along the dashed line in Figure 2, where each movement towards the origin implies proportional contraction of all inputs (radial contraction). The further a firm is from this IQ curve, the larger proportional reduction in inputs is possible, and therefore the firm is less technically efficient. Farrell (1957) defines *input–based technical efficiency* as the ratio of the minimum input bundle to the observed bundle, given a level of output.

Figure 2. Farrell input-based efficiency measure



Technical efficiency is not the only concern in terms of efficient performance. An additional criterion demands not only obtaining the maximum output from minimum inputs, but also minimizing the total production costs. This demand is called the *allocative efficiency*. The implication of this additional criterion is that it is required to remain on the isocost (*IC*) line for a given the level of intended output. The slope of *IC* is equal to the ratio of relative input prices (prices of non-energy input to energy input). A firm is said to be both technically and allocatively *efficient* if, and only if, it is located at the point where curves *IQ* and *IC* are tangent (for example, at point x^{**} in Figure 2). Schmidt and Lovell (1979) and Kumbhakar and Lovell (2000) used efficiency measures of this type that reflect both technical and allocative efficiency by using a cost frontier model. For instance, the cost-minimizing energy demand frontier can be derived given the technology available. Then, energy inefficiency is measured as the distance between the observed energy use and the level stipulated by the cost minimizing energy demand frontier. Formally, *overall efficiency* is defined as the product of technical efficiency and allocative efficiency.

In addition to the radial measure proposed by Farrell (1957), there are also non-radial measures to evaluate efficiency (e.g., Kopp, 1981; Kumbhakar and Lovell, 2000). For instance, energy efficiency can be measured based on non-radial contraction of input energy, while output and non-energy inputs are held constant. Then, energy efficiency scores reflect the maximum possible reduction of energy input only, keeping all other factors the same.

In this thesis, the energy efficiency measure is obtained using the cost frontier model suggested by Schmidt and Lovell (1979) and Kumbhakar and Lovell (2000). This model has been a natural choice when the focus is on input choice (e.g. energy) and the objective is to minimize costs for given level of output (Kumbhakar et al., 2015). Derivation of cost frontier model is discussed in details in e.g. Kumbhakar and Lovell (2000).

2.2 Frontier Analysis

Today, frontier methods are widely used in benchmarking analyses. The main idea is to model the frontier of the technology representing the best practice technology rather than modeling the average use of the technology (Bogetoft and Otto, 2011). There are two main approaches to model the frontier: stochastic frontier analysis (SFA) and data envelopment analysis (DEA). Both approaches construct a frontier, although there are fundamental differences in the principles on which they construct this frontier. SFA is a parametric approach that makes prior assumptions about technology. It is also stochastic approach that allows for factors outside the control of the firm, which implies that not all deviation from best performance will be attributed to inefficiency — some of it will be statistical noise. In contrast, DEA is a non-parametric approach, meaning that there are minimum prior assumptions made about technology. It is also deterministic, because it does not allow for any statistical noise. Therefore, any distance from the frontier is labeled as inefficiency.

Whether to use SFA or DEA depends on whether one wants to have technology be flexible, or whether one wants noise separation. The quality of data and any specific interest about explaining underlying factors of inefficiency will play roles in choosing DEA or SFA. Empirically, DEA may be used whenever a flexible technology is preferred, while SFA is preferred dealing with “noisy” data.

2.2.1 Stochastic Frontier Analysis (SFA)

SFA can be traced back to two papers published simultaneously by Meeusen and Broeck (1977) and Aigner, Lovell, and Schmidt (1977). These papers used SFA to model a stochastic production frontier and assumed that output levels depended on technical inefficiency as well as random shocks outside a firm’s control, such as variation in weather. The objective of the SFA model was to estimate the production technology as well as the technical inefficiency for each firm. These models were called “composed error models” because the error term had two stochastic components, namely inefficiency and random noise. This separation was possible because of the distributional assumptions for these two components. Random noise is usually assumed to have a normal distribution, while inefficiency is assumed to have a one-sided and non-negative distribution.

The half-normal distribution is the most common assumption for the one-sided inefficiency terms in empirical studies. However, there are alternative distributions for the inefficiency term such as the truncated normal distribution suggested by Stevenson (1980), the exponential distribution suggested by Meeusen and Broeck (1977), and the gamma distribution proposed by Greene (1980). The one-sided and non-negative nature of the inefficiency term results in an error term that has an asymmetric distribution. Meeusen and Broeck (1977) and Aigner, Lovell, and Schmidt (1977) used a Maximum Likelihood Estimator (MLE) to estimate inefficiency by obtaining the joint density of independently distributed inefficiency and random noise terms, using their distributional assumptions and an assumption of their independence.

A key concern in the SFA model is whether distributional assumptions of the one-sided inefficiency terms have substantial implications for results. To address this concern, Greene (1990) compared average inefficiency levels across the four main distributional specifications for the one-sided inefficiency term (half normal, truncated normal, exponential, and gamma) and found that there was almost no difference in the average inefficiency for 123 US electric utility providers.

In this thesis, I use SFA in Papers [I] and [III] to estimate the energy efficiency. In these papers, a half-normal distribution is assumed for the one-sided inefficiency term. There are few other studies which used SFA to estimate energy efficiency (see for example Boyd 2008, Buck and Young 2007, Filippini and Hunt 2011, Zhou et al. 2012, and Lundgren et al. 2016).

2.2.2 Data Envelopment Analysis (DEA)

DEA was introduced by Charnes, Copper, and Rhodes (1978) as a linear programming technique to measure the efficiency of firms. DEA uses observed data points (input-output combinations) to construct the frontier presenting the best practices. In contrast to SFA, DEA does not allow for statistical noise and random shocks outside the control of firms, and therefore any deviation from the frontier is considered to result from poor performance and/or inefficiency. Also, SFA estimates the conditional mean of inefficiency, while DEA provides an upper bound for efficiency. DEA has the advantage that it does not require any assumptions about the functional form of the technology or the distribution of the error term, and model misspecification is therefore not a concern. Indeed, DEA requires an assumption regarding the production function by specifying degree of returns to scale. However, efficiency scores obtained by DEA are sensitive to sample variation and data outliers.

Recent examples of empirical studies applying DEA to calculate energy efficiency include Ramanathan (2000), Hu and Wang (2006), Azadeh et al. (2007), Mukherjee (2008a, 2008b), Shi et al. (2010), and Bloomberg et al. (2012), Zhang et al. (2016). However, most of these studies do not consider generation of undesirable outputs in their measurement of energy efficiency. In this thesis, we use DEA in Paper [II] to measure the energy efficiency, where we consider production of undesirable outputs (e.g. emissions) in order to appropriately credit firms for their abatement activities, which is done using the joint production technology framework proposed by Färe and Grosskopf (2004).

2.3 Data

The empirical analyses in this thesis are based on detailed unbalanced firm-level panel datasets for the Swedish manufacturing industry. The datasets generally fall in the period 1997–2008.

Although each paper in this thesis adopts different variables, sectors and time frames, the aggregate of data used in this thesis was collected by Statistics Sweden (SCB) and covers all sectors (14 total) in the Swedish manufacturing industry. The 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 four sectors *Basic iron and steel*, *Chemical*, *Pulp and paper*, and *Mining* are considered heavy, or energy intensive industries, and consume about 75 percent of total energy used by the manufacturing industry (Swedish Energy Agency (SEA) and SCB, Report 2015).

The full dataset contained firm-level information about costs and quantities that are related to different production inputs like labor, capital, and energy. Labor was the number of full-time employees. Capital stock was calculated using gross investment data (excluding investments in buildings) by the perpetual inventory method, which used the sum of gross fixed capital formation in previous years as well as the depreciation rate of capital (determining service life of the capital) and estimated gross and net capital stock for a time series. Energy input was aggregated from electricity, oil, gaseous fuel, coal, biofuel, and district heating, and converted to energy equivalents measured in Gigawatt hours (GWh) using the same conversion rates for all industries. The output index was calculated as the firm's final sales divided by its corresponding producer price index for a given sector. Firm level input prices were calculated by the ratio of input cost to quantity used. For instance, yearly salary (labor price) for each firm and year was calculated by the ratio of total salaries paid to employees in that year to number of employees. Therefore, the salary variable did not reflect factors like the contribution of part-time salaries. Instead, it reflects the average amount paid to an employee in each year. The capital price was defined as the user cost of capital and was calculated based on national and sector-level indices (Lundgren,1998; Brännlund and Lundgren, 2010).

The dataset also included firm-level measures of emissions of CO2, SO2 and NOx measured in metric ton, and policy related measures such as participation in the European Union Emission Trading System (EU ETS)[2] and environmental related firm-level investments and expenditures. The dataset covered the first phase of emission trading system (2005–2007) as well as the first year of the second phase (2008).

The data for environmental related investments and expenditures (EIE) at firm-level were based on the 'environmental protection expenditure in industry' survey. This survey has been conducted since 1999 by Statistics Sweden, with compulsory participation starting in 2001. EIE includes a sample of firms with at least 20 employees, and covers three main categories: pollution treatment investment, pollution prevention investment, and current expenditure. Pollution treatment investments do not affect the production process and aim to only deal with pollutants that are already made; these types of solutions are often referred to as 'end-of-pipe' solutions (Jaraite et al., 2014). Filters, scrubbers, and protection of ground water resources from landfill leakage are examples of such investments. In contrast, pollution prevention investments aim to directly affect production process and decrease pollution. These investments "are characterized by: (1) lowering emissions from production processes; (2) facilitating the use of less environmentally damaging input factors; (3) new and more efficient and less emitting equipment and machinery" (Jaraite et al., 2014, pp. 164). Optimizing the use of chemicals, increasing recycling, and use of less polluting inputs to reduce

[2]EU ETS is the world's first major carbon trading market and the major EU's policy tool to combat climate change and reduce greenhouse gas emissions cost-effectively (European Commission, 2010). Four trading phases of the EU ETS were designed so far. First phase that lasted from the launching of the EU ETS in 2005 to the end of 2007. Second phase that began in 2008 and ended in 2012. Third phase is still ongoing (2013–2020) and the fourth will cover the years 2021–2030. These phases are governed by the EU ETS Directive and the secondary legislation.

waste toxicity are examples of such investments. The survey data on pollution treatment and prevention costs each contain disaggregated information on air, water and waste. Lastly, current expenditure refers to some costs that are not considered to be investments, but that are linked to pre-existing equipment or operational activities. For instance, current expenditure can include costs of personnel, external hiring of services to clean up land, and material and energy used for existing environmental facilities and their management. These costs are divided into internal costs and hired services. Financial costs such as depreciation and environmental taxes and fees are not included (Jaraite et al., 2014).[3] For the time period 2001–2008, the share of EIE in relation to a firm's total production costs was low, on average less than 3% across all manufacturing sectors. EIE varied on a large scale between sectors, averaging from 0.52% in *Electro* up to 5.55% in the *Pulp and paper*. However, the time variation was relatively low, averaging between 2.30% and 2.89% over the period 2001–2008 .

The empirical analyses in this thesis used different sample periods, sectors, and variables. For Paper [I], the focus was on Swedish heavy industry, i.e., *Basic iron and steel*, *Pulp and paper*, *Chemical* and *Mining* during the period 2000–2008. Papers [II] and [III] covered the period 1997–2008 and all 14 sectors in the Swedish manufacturing industry. The analysis in Paper [IV] covered the period 2001–2008 and 11 sectors in the manufacturing industry. This choice of time is mainly driven by the availability of survey data on EIEs from 2001 to 2008. The SCB survey methodology for the EIE data changed after 2008, which means that including more recent years would have introduced inconsistencies in the production data. Hence, Paper [IV] includes no data after 2008. Furthermore, three sectors (*Fabricated metal products*, *Mining*, and *Printing*) were excluded from the analysis in Paper [IV] because there were not enough number of observations.

[3] For more detailed explanation of the data on environmental investment and expenditure and examples see Jaraite et al. (2014).

3 Summary of the Papers

In addition to an introductory part, this thesis consists of four self-contained papers in which I address the implications of energy efficiency improvements and environmental regulations for industrial energy and labor demand. The four papers belong to two main themes. Papers [I - III] are on the topic of energy efficiency and energy rebound effect which has implications for industrial energy demand. In Paper [IV], the focus turns from input energy to labor where I investigate how (or indeed even whether) the environmental regulations affect labor demand. Hence, this section provides a background on the two main themes, followed by a summary for each paper.

3.1 Energy Efficiency Improvement and the Rebound Effect

Energy efficiency improvement (EEI) refers to the possibility of producing the same amount of goods and services using less energy, or producing more goods and services using the same amount of energy. Hence, one would expect that EEI reduces energy consumption (and also emissions) per unit of production.

Despite this intuitive expectation, as long ago as the middle of the 19th century, the English economist William Stanley Jevons noticed that the invention of more efficient steam engines increased industrial use of coal. He argued that "*It is a confusion of ideas to suppose that the economical use of fuel is equivalent to diminished consumption. The very contrary is the truth*" (Jevons 1865, Chapter VII.3). The mechanism behind this paradox is that when technological progress takes place, it improves the efficiency in the use of energy (e.g., fuel), but with the consequence that the real unit price of energy service drops, meaning that energy becomes relatively cheaper to use, which subsequently initiates a behavioral or re-optimizing response in terms of energy demand. This pattern is called the *energy rebound effect*. This effect appears in the form of substitution and output/income effects, and it may change the expected energy and emission savings in relation to the potential calculated by strict engineering principles (without re-optimizing). Indeed, the energy rebound effect may increase, decrease, or even offset expected energy and greenhouse gas (GHG) emission savings. Because of the rebound effect, the impact of EEI on final energy use and GHG emission savings is ambiguous and remains an empirical question. The size of the effect is measured as the difference between expected and actual energy savings due to EEI, which can be obtained by estimating the elasticity of demand for energy with respect to changes in energy efficiency (Saunders, 2000).

There are both global and national concerns about climate change and pollution, which have led to both short- and long-term policy targets. Of course, policy makers must balance competing economic and environmental interests. Environmental policies like taxes or quotas might cause economic distortions that could reduce industry competitiveness and have other unintended negative effects. On the other hand, promoting EEI allows for the same level of energy service but by using less energy, which would mean a smaller impact on climate, and for this reason, policy makers are often in favor of promoting EEI. For instance, the European Union (EU) has set targets for 2030 to reduce GHG emissions by 40% (from 1990 levels) and to reduce energy consumption through EEI by at least 32.5%, relative to a 'business as usual' scenario. However, policy makers may be too optimistic about energy and emission savings, and not take the rebound effect into account, which makes the effect of EEI less certain in practice.

There are five possible scenarios for the size of the energy rebound effect. First, *backfire* names the effect seen in the Jevons paradox, and is when the response to EEI more than offsets the expected energy savings from EEI (negative energy savings). Second, *full rebound* refers to an outcome where the response to EEI exactly offsets the expected energy savings (zero energy saving). Third, *partial rebound* is when EEI leads to positive energy savings, although not the full potential calculated from engineering principles. Fourth, *zero rebound* happens when there is no behavioral response to EEI and actual energy savings are equal to the expected level (corresponding to the engineering calculation). Finally, *super-conservation* is the scenario in which responses to EEI increase the expected energy savings more than the potential from an engineering calculation.

Rebound effect is generally welfare-enhancing and economically beneficial as it indicates that firms re-optimize their choices of inputs based on a change in relative input prices and real income (*substitution/intensity* and *scale/output* effects), which creates economic values. That said, the size of the rebound effect must be considered when energy-related policies addressing climate change and energy demand are set, or when the effectiveness of energy efficiency policies are evaluated. For instance, if the energy rebound effect is large and the aim is to commit to a certain level of emissions, efficiency gains should be coupled with complementary policy actions to keep the cost of use the same (or higher) to avoid the Jevons paradox, or backfire.

Papers [I] and [II] in this thesis measure the size of the energy rebound effect due to EEI at the industrial sector level, as well as the relative energy efficiency scores. Paper [III] estimates the short- and long-term energy efficiency scores for the Swedish manufacturing industry. Papers [I – III] are summarized below.

3.1.1 Paper [I] The Rebound Effect in Swedish Heavy Industry

The energy rebound effect is a response to EEI which may change the energy and emission savings expected from efficiency improvements. EEI generally increases the energy service obtained from the energy unit, which lowers the real unit price of energy service for producers and makes energy relatively more attractive as an input. Hence, producers may substitute energy input for other inputs, and this is referred to as the intensity effect. Furthermore, the cost savings due to this substitution may be used to increase the output level, referred to as output effect. The size of the energy rebound effect depends on the intensity and output effects.

In this paper, we estimate the fuel and electricity rebound effects for the four most energy-intensive sectors in Swedish manufacturing industry, i.e. heavy industry: *Basic iron and steel*, *Pulp and paper*, *Chemical*, and *Mining*. Our empirical analysis is performed at sector level using a detailed firm-level panel data for the period 2000–2008. Fuel and electricity efficiency scores and the rebound effects are estimated simultaneously using SFA. This paper aims to provide answers to the following specific questions: i) What are the size of fuel and electricity rebound effects in heavy industry? ii) Are there heterogeneous responses to EEI among firms within each sector, and can we identify some determinants of those responses?

The rebound effect could be obtained theoretically by using the elasticity of demand for energy services[4] with respect to EEI (Saunders, 2000). To estimate this elasticity, we first derive stochastic fuel and electricity demand frontiers in the spirit of the cost-minimizing input demand equations (in Schmidt and Lovell, 1979 and further discussed in Kumbhakar and Lovell, 2000) based on a Cobb-Douglas (C-D) production technology.[5] The derived fuel and electricity demand frontiers indicate the minimum level of electricity and fuel required to produce a level of output, given the technology, input quantities and prices. Second, we integrate the rebound effect into stochastic fuel and electricity demand frontiers by adding an interaction term with the inefficiency term, as proposed by Orea et al. (2015), where this term includes a parameterized rebound effect function. Then, the fuel and electricity efficiency scores and their rebound effects are estimated simultaneously for each firm and year using MLE. The scores give how much the use of fuel and electricity can be decreased given the output level and the amount of non-energy inputs. This process is in line with efficiency measures proposed by Schmidt and Lovell (1979) and Kumbhakar and Lovell (2000) while taking costs into account. These scores reflect both technical and allocative efficiencies in use of energy.

The results show that partial fuel and electricity rebound effects exist in all four studied sectors, implying that the expected energy and emission savings due to EEI are not totally offset by the rebound effect. Hence, promoting EEI could be justified for achieving environmental and energy saving targets. This

[4] 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).

[5] A C-D is assumed due to its simplicity in deriving the demand frontier (Kumbhakar and Lovell, 2000). A cost minimization approach is a natural choice because in a cost minimization case, the focus is on input use (here, fuel and electricity use) given a certain level of output.

study also suggests that CO_2 intensity and fuel and electricity share are useful indicators for identifying firms with higher or lower rebound effects within each sector. For instance, our results suggest that in each sector the rebound effect is lower among the relatively more polluting firms. Depending on whether the policymakers' priorities are to boost the economy or mitigate the climate impacts, our results also suggest which sectors should be prioritized in terms of promoting EEI. For instance, if reduction of GHG emissions is the priority, our results suggest that *Basic iron and steel* becomes particularly important for promoting EEI, because CO_2 emission saving from an EEI is almost four times larger than a similar initiative within *Pulp and paper*, and more than twice as large as it could be for the other three energy intensive sectors together. On the other hand, if energy saving is the greatest concern, our results suggest that the largest total energy savings are to be found in *Pulp and paper*.

It should be noted that using SFA to estimate rebound effects has several advantages compared to previously used approaches. SFA provides a direct measure of the rebound effect, as it directly estimates the elasticity of demand for energy with respect to EEI. In contrast, earlier studies measured this effect indirectly through different elasticities as proxies, such as the own-price elasticity of demand for energy. However, due to the general characteristics of the error term in SFA models, SFA does not allow for a full range of potential rebound effect estimates. Indeed, it excludes the possibility for both *full rebound* and *backfire* responses, and overall rebound effect may hence be underestimated. The convergence of the MLE is also very sensitive to the variables included in the rebound function as determinants which motivates an alternative approach for estimating rebound effects. This motivation is the starting point for Paper [II].

3.1.2 Paper [II] A Dynamic Analysis of Industrial Energy Efficiency and the Rebound Effect

Although there is a broad consensus that an energy rebound effect exists, there are significant differences of opinion about how to measure it. As mentioned earlier, following Saunders (2000), measuring this effect seems straightforward because it only requires an estimate of the elasticity of demand for energy services with respect to changes in energy efficiency. However, estimating this elasticity is not easy due to the lack of appropriate data on demand for energy services and/or EEI. Hence, different approaches are used to measure elasticity and the rebound effect.

In this paper, we propose a two-stage procedure for measuring both the short- and long-term energy rebound effects. In the first stage, we use DEA to obtain Farrell's input-oriented technical efficiency score for each firm and each year. The scores indicate the maximum possible proportional reduction of all inputs (energy and non-energy inputs) that will produce the same level of desirable and undesirable outputs. The scores are however subject to uncertainty due to sampling variation (Simar and Wilson, 1998), so a bootstrapping approach proposed by Simar and Wilson (1998) is used to obtain biased-corrected efficiency scores. In the second stage, we use bias-corrected scores from stage one to estimate both short- and long-term elasticities of energy demand with respect to EEI by using a dynamic panel data regression model, where this elasticity is a function of firm-characteristic and policy related variables. This function enables us to identify differentiated responses to EEI due to heterogeneity in terms of, for instance, unidentified firm characteristics.

Although Papers [I] and [II] each measure the energy efficiency and rebound effects, they differ in several aspects. In Paper [II], we consider the production of undesirable outputs when we evaluate efficiency in the use of inputs. To do this, we follow the framework and assumptions proposed by Färe and Grosskopf (2004) for a joint production technology where production of desirable (good) outputs create byproducts with negative effects on the environment and humans, referred to as undesirable (bad) outputs. Two assumptions are made in this framework: (i) producing desirable output always generates some undesirable output (the null-joint assumption), and (ii) given a constant bundle of inputs, any reduction of undesirable outputs is conditional on the proportional reduction of desirable outputs (the weak disposability assumption). The weak disposability assumption assumes that the disposal of undesirable outputs is costly. Moreover, the DEA framework requires neither a functional form for the production function, nor any assumption about the distribution of energy efficiency. Indeed, this framework requires an assumption regarding the production function by specifying returns to scale. Furthermore, using a dynamic panel data regression model allows for measuring short- and long-term rebound effect and all different ranges of rebound effects. In terms of the empirical scope, we expand our analysis to all 14 sectors in the Swedish manufacturing industry and the period 1997–2008. This is the first Swedish study to measure both short- and long-term energy rebound effects while taking into account the production of bad outputs.

The results show that the energy rebound effect is best described as *partial* in the short run within majority of manufacturing sectors, which means that the rebound effect mitigates, but does not fully offset, the expected energy and emission savings from EEI. These results to some extent justify the imposed restriction on the range of the rebound effect in Paper [I]. In the long run, the rebound effect however decreases in most of the sectors, implying that within each sector, energy and emission savings due to EEI are larger in the long run compared to the short run. These results further suggest that promoting EEI is beneficial from both environmental and energy saving point of views, not only in the short run but also in the long run. Complementary policies such as energy taxes might be required to obtain the maximum potential emission and energy savings. The results also show that taking into account the bad outputs increases the energy efficiency scores significantly, implying that conventional scores (not accounting for bad outputs) discredit firms for their abatement activities.

Within each sector, the rebound effect is lower among firms with higher energy cost shares in relation to the median energy cost share of that sector. This finding, with some degree of generalization, is in line with the findings of Paper [I] that the rebound effect is lower among more polluting firms.

Depending on how priorities are set among the environment, energy savings, and economic growth, policy makers may choose not only to what extent, but also where to promote EEI, as the rebound effect varies between as well as within sectors. In this paper, we identify sectors where EEI is more likely to have a positive impact on the environment, energy savings and/or sustainable growth (where economic development comes with minimal harm to the environment). How EEI affects the environment, energy savings, and economic growth varies with sector-specific characteristics, such as the level of CO_2 emissions, energy consumption, output per unit of emission, level of energy efficiency, and size of the rebound effect. For instance, our results suggest that EEI in Basic iron and steel has the largest positive effect on the environment, because in this sector, the CO_2 emission savings from EEI are substantially larger than all other manufacturing sectors. Promoting EEI in Pulp and paper leads to the largest energy savings. Finally, EEI in Electro has the weakest negative environmental impact per unit of output.

3.1.3 Paper [III] Is Industrial Energy Inefficiency Transient or Persistent? Evidence from Swedish Manufacturing

Energy inefficiency suggests that the same level of goods and services could be obtained using less energy. Energy inefficiency in a firm may be associated with either long-term structural rigidities in production processes and management, or temporary shortcomings such as misallocation of resources. These two scenarios are referred to as *persistent* and *transient* inefficiencies, respectively, and eliminating them may require different policy measures to address each type.

In Paper [III], I estimate the transient and persistent energy inefficiencies for the Swedish manufacturing industry and evaluate sectors in terms of their potential for energy savings if these inefficiencies could have been eliminated (given the technology available at the time).

The manufacturing industry contributes substantially to the Swedish economy and accounts for about 45% of the total final energy use in Sweden in 2008 (Statistics Sweden (SCB); cited in Martínez and Silveira, 2013). Hence, measuring transient and persistent energy inefficiency for this industry is likely to have implications for the design of energy policies in the short and long run. At present, the available empirical evidence for this industry is limited to a few studies measuring overall energy (in)efficiency such as Lundgren et al. (2016) and Zhang et al. (2016), so the results from this study contribute largely to the empirical literature. Furthermore, because this study is performed at sector level, the results are also potentially interesting for the same sectors in other countries.

I estimate a cost-minimizing stochastic energy demand frontier model with a four-component error term using a firm-level panel dataset covering 14 sectors in the manufacturing industry for the period 1997–2008. The error term captures (i) firm unobserved heterogeneity, (ii) transient or time-varying inefficiency, (iii) persistent or time-invariant inefficiency, and (iv) random noise. All these components can be identified only by making distributional assumptions for the separate terms. A half-normal distribution is assumed for both the transient and persistent inefficiencies, while unobserved heterogeneity and random noise are assumed to follow a standard normal distribution. Estimated energy efficiency scores reflect both technical and allocative efficiencies.

The four-component error term model improves upon earlier SF models because it separates unobserved firm heterogeneity from persistent inefficiency, and transient inefficiency from random noise. The model is also more flexible because it allows for the inefficiency term to be correlated over time, while earlier SF models generally assumed that inefficiencies were independently distributed over time, which is a restrictive assumption (Lien et al, 2018). For instance, a firm may reduce part of its inefficiency over time by removing some of the short-term rigidities. For this estimation, a three-step approach proposed by Kumbhakar et al. (2014) and Lien et al. (2018) was used.

The results in this paper suggest that both transient and persistent energy inefficiencies exist in most sectors of the Swedish manufacturing industry. However, the persistent energy inefficiency is notably larger than the transient, suggesting that energy inefficiencies in this industry are mainly associated with structural rigidities connected to technology and/or management. The results also show that transient and/or persistent energy inefficiencies vary substantially between, as well as within, different sectors. For instance, within a sector, there might be substantial variation in the average point estimates of persistent energy efficiency between groups of firms producing different products.

In terms of overall energy efficiency (in percentages), *Basic iron and steel*, *Textile*, *Chemical*, and *Stone and mineral* were found to have largest potential for EEI. By far the largest potential for energy savings (GWh per year) is found in *Basic iron and steel*; reducing inefficiencies in this sector alone would exceeds the potential savings of the other 13 sectors put together.

3.2 Environment and Jobs

Policy debates sometimes include the claim that there is conflict between jobs and the environment. On the one hand, labor unions and trade groups argue that environmental regulations impose extra costs to firms, which results in a reduction in production and demand for labor. One the other hand, there are arguments in favor of the concept of 'green jobs', which may solve challenges associated with both climate change and the high rates of unemployment in many industrialized countries. Empirical evidence for and against both of these claims is mixed. Some studies find no substantial effects of environmental regulations on employment, while others find that environmental regulations have negative impacts on employment. It has also been noted that although there might be limited net employment effects of environmental regulations, the effect on the structure of the economy may be substantial, since there may be a shift from "brown" to "green" jobs (Greenstone, 2002). However, this re-composition of labor can still be beneficial to society as a whole. Paper [IV] investigates the impacts of a marginal change in environmental expenditure and investment on sector-level employment, and this paper is summarized below.

3.2.1 Paper [IV] Environment versus Jobs: An Industry-level Analysis of Sweden

Environmental management costs (EMC) can be defined as the sum of environmental expenditure and environmental investment. In this paper, I investigate whether a marginal change in EMC has an effect on demand for labor in the Swedish manufacturing industry. No previous empirical study has been done on the relationship between environmental related costs and labor demand at sector level for the Swedish manufacturing industry — the majority of contemporary and historical empirical evidence comes from the U.S., and whether those results can be properly applied to European countries is unclear. Hence, it is hoped that this study will contribute to policy design and provide insights regarding the effects of EMC on industrial labor demand.

I use the general framework proposed by Morgenstern et al. (2002) to estimate the effect of a marginal increase in EMC on sector-level labor demand. It is assumed that firms are cost-minimizing with respect to two distinct activities: conventional production activities (to produce marketed goods) and environmentally related activities (to produce an environmental output). The total cost is the sum of production costs and EMCs.

The hypothesis underlying this research is that an increase in EMC will initiate a sequence of changes that may ultimately change the demand for labor. At the firm level, if holding the output level constant, abatement activities should increase the demand of all inputs, including labor. This process is referred to as the *cost effect*, and it has a positive effect on demand for labor. Engaging labor in pro-environmental activities (other than production) may change the level of labor intensity, meaning that the production of output and environmental goods in total may become more or less labor intensive than "conventional" production. This process is referred to as the *factor shift effect*, and the implications of this effect for labor demand is an empirical question. At the sector level, the change in demand for labor is obtained by aggregating firm-level effects. Higher production cost (induced by environmental regulation) increases the output price and reduces the demand for output, and hence demand for all the inputs including labor. This process is referred to as the *demand effect*, and the influence on labor depends on the extent to which the increased costs are passed on to the consumers, and the price elasticity of the aggregate output demand. The total impact of EMC on the aggregate labor demand at sector level is obtained by summing the cost effect, the factor shift effect and the demand effect.

To estimate the aggregate factor shift effect, I derive a system of cost-minimizing input cost shares by differentiating the logarithm of the cost function with respect to the logarithm of input prices. Each input cost share reflects the costs associated with the use of that input in both environmental activities as well as conventional production activities. For each firm and year, the sum of input shares adds up to unity. Furthermore, homogeneity constraints are imposed by normalizing the input prices. I use a detailed firm-level panel data for 11 sectors in the Swedish manufacturing industry during the period 2001–2008 and estimate an input cost share system using a three-stage least squares (3SLS) estimator, while assuming cross-equation symmetry conditions and homogeneity of degree one in prices.

To obtain the demand effect, an estimate of the price elasticity of the aggregate output demand is required. As there is no empirical estimate of this elasticity for the Swedish manufacturing industry, I perform a sensitivity analysis for the total net effects given different elasticities.

The results indicate that within each sector a marginal change in EMC does not affect employment substantially. However, the sign and magnitude of the net employment effects depends strongly on the aggregate sector-level output demand elasticity. For an inelastic output demand, a marginal increase in EMC has a small positive net impact on employment, while a more elastic output demand leads to a negative, but in most sectors relatively small, net effect on employment. In summary, the results do not generally show any substantial trade-off between jobs and the environment. However, due to the absence of empirically estimated demand elasticities, the general policy recommendation from this study is still to adopt a careful attitude regarding Swedish environmental initiatives for sectors exposed to world market competition.

4 Conclusions and Future Research

Measuring the effects of energy efficiency improvement (EEI) and environmental management costs (EMC) on industrial energy and labor demand has been the core of this thesis. The empirical analyses suggest that there is room for EEI in most sectors within the Swedish manufacturing industry. Furthermore, the results suggest that the main source(s) of overall energy inefficiency are persistent rather than transient, implying that inefficiencies are a problem in the long term, and mainly related to structural rigidities connected to technology and/or management issues. That said, transient, persistent, and overall energy inefficiencies vary substantially between, as well as within, different sectors.

The results also suggest that energy rebound effects are substantial, implying that the expected energy and emission savings from EEI are counteracted. However, the rebound effect does not fully offset the expected savings. Furthermore, the energy rebound effect is welfare-enhancing, because it shows that firms are re-optimizing to changes in relative input prices (Borenstein, 2015). That said, the size of the rebound effect should be taken into consideration when evaluating the effectiveness of energy efficiency policies addressing climate change and energy demand. The results show that the long-term energy rebound effects are smaller than the short-term effects in most sectors. This implies that within each sector, energy and emission savings due to EEI are larger in the long run compared to the short run.

The findings also suggest that the rebound effect varies considerably between and within sectors. The results indicate that different firm characteristics matter for the variation of the rebound effect. For instance, findings show that within each sector, the rebound effect is lower among the relatively more polluting firms and firms with higher energy cost share. This result implies that policies promoting energy efficiency in order to address emissions and/or energy savings are likely to be more effective if applied to such firms.

This thesis identifies sectors where EEI is more likely to have a positive impact on the environment, energy savings and/or sustainable growth (where economic development comes with the least negative environmental impact). For instance, our results suggest that EEI in *Basic iron and steel* has the largest positive effect on the environment, because in this sector, the CO_2 emission savings from EEI are considerably larger than all other sectors. Promoting EEI in *Pulp and paper* leads to the largest energy savings. Finally, EEI in *Electro* has the least negative environmental impact per unit of output produced.

Our research shows no evidence that a marginal change in EMC results in a trade-off between the environment and jobs in the Swedish manufacturing industry. The results show that the sign and magnitude of EMC on employment ultimately depends on the aggregate sector-level output demand elasticity. If aggregate output demand is inelastic, EMC has small positive net effect on labor demand. A highly elastic demand scenario generally suggests small negative net effects on employment. Hence, marginal change in EMCs are unlikely to lead to major job losses unless the aggregate output price elasticity of demand is considerably high, which could be the case in, for instance, some sectors exposed to world market competition.

From a methodological point of view, an important take-away from this thesis is that the results from efficiency analysis are sensitive to not only the choice between SFA and DEA, but also to the assumptions within each approach. For instance, in DEA, the choice of returns to scale may have had implications for the efficiency scores. In SFA, the choice (i) between a four-component SFA model separating persistent and transient (in)efficiency or earlier SFA model estimating only the overall (in)efficiency, (ii) distributional assumptions for the (in)efficiency term, and (iii) the functional forms of production technology may have had effects on the results.

Future research could be carried out to identify policy measures at the sector-level for improving persistent and transient energy efficiencies for the Swedish manufacturing industry in order to meet energy and climate related targets.

A complete assessment of the net total effects of environmental regulation on employment is left for future research. In particular, the next step would be to trace the structural shift from “brown” to “green” jobs among the Swedish manufacturing sectors. As a response to environmental regulations in some sectors, labor may become employed elsewhere (Greenstone, 2002). Estimating aggregate output price elasticity of demand at sector-level also remains an important area for future studies of the “jobs versus the environment” question.

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