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Energy Intensity and Convergence in Swedish Industry: A Combined Econometric and Decomposition Analysis

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Abstract

This paper analyzes the determinants of energy intensity and tests for convergence across 14 Swedish industrial sectors. The analysis builds on a non-parametric regression analysis of an intensity index constructed at the industry sector level as well as indexes constructed from a decomposition of this index. The latter isolates two key determinants of changes in energy intensity and convergence patterns: energy efficiency improvements and changes in economic output (activity). The empirical analysis relies on a detailed sectorial dataset covering the period 1990-2008. The findings indicate that input prices, including the price of energy, have been significant determinants of energy intensity in the Swedish industrial sectors. This effect can primarily be attributed to the efficiency channel and with a less profound influence from the activity channel. These results suggest that a well-designed tax system could be effective in delivering significant energy efficiency improvements in Swedish industry. We also find evidence of energy intensity convergence among the industrial sectors, and this primarily stems from the activity channel rather than from the efficiency channel. The above implies that during the studied time period Swedish industry shifted away from more to less energy-intensive production, in part perhaps driven by moving energy-intensive manufacturing abroad.

Keywords: energy intensity; convergence; index numbers; decomposition; industrial sectors.

JEL Classification: C14, O13, O47, Q43.

1. Introduction

Environmental and energy security concerns have generated great interest in issues related to the decoupling of environmental pollution, particularly carbon dioxide emissions, from economic growth. This has in turn resulted in a renewed interest in the relationship between energy and output, especially the use of fossil fuels and how to use energy resources efficiently. It is generally acknowledged that investments in new energy efficient technologies will play a significant role in achieving both environmental objectives and objectives concerning energy security. The industrial sector plays an important role in this context; it accounts for about one third of global final energy use and this share has grown over time (International Energy Agency, 2012). For this reason it is imperative to gain an in-depth understanding of the determinants of energy intensity – the ratio of energy use to output – in the industrial sector, not the least the extent to which changes in industrial energy intensity result from structural shifts in the industry or rather from more fundamental improvements in the industry's use of different energy carriers. This should provide important information for decision-makers on the design and evaluation of policy instruments aimed at achieving further energy efficiency improvements and the reduction of the carbon footprints associated with energy use.

Beyond this, a number of previous studies have illustrated the relevance of energy intensity convergence across countries, either in the aggregate and/or across sectors between countries and/or across sectors within the same country. Cross-country convergence in energy (as well as carbon dioxide) intensity could influence the political economy of negotiating multilateral climate agreements (e.g., Pettersson et al., 2014). For instance, evidence of energy intensity convergence could indicate that specific countries would only need limited special consideration for global agreements to be considered fair (Liddle, 2010). A related argument may be valid also for the study of energy intensity convergence across industrial sectors in one country, especially concerning the consequences for different sectors of climate and energy policies. Such inter-sector convergence may arise due to different spillovers across sectors, both technological (e.g., improvements in the energy efficiency of generic production processes such as fuel combustion) as well as managerial (e.g., the use of energy management systems). There may be a need to provide evidence on the level of knowledge transfer across sectors, especially from leading sectors to backward sectors in terms of energy intensity, and use this information in targeting public support for energy efficient R&D activities. Finally, investigating energy intensity convergence between industrial sectors within a single country may also provide knowledge of what one may expect concerning future convergence at the international level (see also Brännlund et al., 2015). Countries with similar industry structures may be more likely to converge in terms of energy intensity, while the opposite could hold for countries with heterogeneous industrial compositions.

Empirical studies on industrial energy use, output and the environment can be grouped into three main categories. The first category focuses on investigating trends in energy use, energy intensity and emission intensity, as well as on the determinants of energy intensity (e.g., Bernstein et al., 2003; Fisher et al., 2004; Metcalf, 2008; Neelis et al., 2007; Nilsson, 1993; Schipper et al., 2001; Worrell, 2004). The general conclusion from much of this work is that energy intensity and energy use have tended to decline over time, although the specific trends have been contingent on the time periods and the industrial sectors under study. Studies that have focused on the determinants of energy intensity have typically pointed out the importance of energy price changes (e.g., Bernstein et al., 2003; Fisher et al., 2004; Metcalf, 2008). Other important determinants of industrial energy intensity are capacity utilization, the climate, R&D expenditures, the structure of the economy, ownership patterns etc. (e.g., Bernstein et al., 2003; Fisher et al., 2004).

The second category of studies focuses on index number decomposition analysis (e.g., Duro et al., 2010; Greening et al., 1997; Howarth et al., 1991; Huntington, 2010; Liu and Ang, 2007; Metcalf, 2008; Mulder and de Groot, 2012; Mulder et al., 2014; Sue Wing, 2008). The study by Howarth et al. (1991) used the Laspeyres method to examine trends in manufacturing energy use in eight OECD countries over the period 1973-1987. These authors decomposed changes in energy use into activity, structure and intensity effects and found that structural changes had led to modest reductions in energy use for almost all countries. Overall, they found energy intensity to decline over the period for each of the countries. Mulder and de Groot (2012) also found that across countries the energy intensity level decreased for both the manufacturing and the service sector, respectively, although the rate of decrease in the service sector was relatively low. Their decomposition analysis showed that a significant share of the decrease in aggregate energy intensity could be attributed to changes in the sectoral composition of the economy. Other studies within this category have provided related evidence of decreasing energy intensity at the country and/or sector levels. Sue Wing (2008) combined decomposition and econometric analyses to explain the declining energy intensity in the U.S. economy, and attributed most of the observed decline to inter-industry structural changes, and with energy efficiency improvement only playing a significant role post 1980.

The third category of studies comprises research on energy convergence and energy productivity/intensity convergence (e.g., Ezcurra, 2007; Liddle, 2010; Markandaya et al., 2008; Miketa and Mulder, 2005; Mulder and de Groot, 2007, 2012). The results from these studies generally support the convergence hypothesis, i.e., that backward countries and sectors in terms of energy intensity tend to catch-up with leading countries and sectors. Most of these studies have tested for convergence in aggregate energy intensity across countries (e.g., Ezcurra, 2007; Liddle, 2010; Markandaya et al., 2008) or for different industrial sectors across countries (e.g., Miketa and Mulder, 2005; Mulder and de Groot, 2007, 2012). However, so far no study has examined convergence in energy intensity across industrial sectors within an individual country, irrespective of the fact that such information could be useful for within-country energy policy design in terms of energy efficiency targets and government support of R&D and knowledge transfer across sectors.

The objective of this study, which relates mostly to the second and third categories of studies, is twofold. The first is to provide evidence on the determinants of energy intensity across different manufacturing sectors in Sweden. The analysis addresses the roles of the energy price, R&D intensity, capacity utilization as well as the prices of capital and labor inputs, respectively. The second objective is related to understanding the differences in energy intensity dynamics across the manufacturing sectors in the country. Specifically, we are here interested in testing the so-called beta convergence hypothesis, and analyze the extent to which changes in energy intensity and convergence result from structural shifts in the industry or rather from more fundamental improvements in the use of energy.

In contrast to most previous research in the field the analysis builds on a non-parametric regression analysis of an intensity index constructed at the industry sector level as well as indexes constructed from a decomposition of this index. The energy intensity indexes are based on the Fisher ideal index analysis (Fisher, 1921), and these isolate two key determinants of changes in the energy intensity and convergence patterns: energy efficiency improvements and changes in economic output (activity). An important difference from most previous studies is that we combine decomposition analysis with regression analysis to examine the determinants of both energy intensity and energy intensity convergence.

Previous studies that have combined decomposition and regression analyses in the energy literature are Metcalf (2008), Mulder and de Groot (2012), and Sue Wing (2008). Still, Metcalf (2008) and Sue Wing (2008) only focused on energy intensity determinants and trend analysis, respectively, whereas Mulder and de Groot (2012) focused on trend and energy convergence of similar sectors across countries. Our study differs from these in the sense that: (a) we examine both the efficiency and activity channels for the determinants of both energy intensity and convergence in energy intensity across sectors; (b) we consider manufacturing sectors within a given country; and (c) we implement a full non-parametric methodology to examine the drivers of energy intensity and test for convergence of energy intensity. The advantage of employing a non-parametric approach is that we avoid the imposition of functional specification bias.

The choice of Sweden for this study is motivated by the fact that we have access to a detailed sectorial level dataset that enable analyses of the drivers of energy intensity and the growth rate in energy intensity in a consistent and reliable way, i.e., with minimal data inconsistencies and aggregation issues. This data set covers 14 manufacturing (industry) sectors over the time period 1990-2008. Another reason is that in Sweden energy use by industry is a major contributor to both total final energy use and the gross domestic product (GDP). In 2013, the Swedish industrial sector contributed to about 38% of total final energy consumption in the country (Swedish Energy Agency, 2015), and this puts Sweden among the top-five countries in the European Union (EU) in terms of industrial energy use as a share of final energy consumption. This also indicates the energy policy relevance of the industrial sector in Sweden, and the implications this sector has for the country's contribution to the 27% energy efficiency EU-level target. Moreover, Sweden has had an active climate and energy policy for a fairly long time, including significant changes in carbon and energy taxes over the last three decades. For instance, the Swedish carbon dioxide tax (including some deductions for energy-intensive industrial sectors) was introduced already in 1991 (Brännlund et al., 2015). Against this background, Sweden should serve as an interesting case study to analyze industrial energy intensity dynamics and test for energy intensity convergence across different manufacturing sectors.

The remainder of the paper is structured as follows. In the next section we derive our energy factor demand model from production theory; we relate this to energy intensity in order to establish some key determinants of energy intensity. We also discuss the theoretical underpinnings of energy intensity convergence, especially the channels through which convergence (or divergence) may appear as suggested in previous research (e.g., see Grossman and Helpman, 1991, for economic growth convergence). The empirical model for the analysis is also presented in section 2. The data used are presented and discussed in section 3. In section 4 we present the results, while section 5 contains the conclusion of the study and points at some important implications.

2. Theoretical and methodological issues

The theoretical background for our derived input demand model, and ultimately our energy intensity variable, is production theory. We assume that each firm in an industry combines capital, labor and energy inputs to produce a given level of output. In order to derive the determinants of energy intensity for a given industrial sector, we formulate a fully flexible cost function. This differs from related studies (e.g., Fisher-Vanden et al., 2004) using less flexible specifications such as the Cobb-Douglas cost function, We do not impose a specific functional form, but rather assume a general model specification in which the function is determined from the underlying data generation process (DGP) via a nonparametric approach. This has the advantage of reducing functional misspecification bias. The general total cost (*C*) function is expressed as:

$$\mathrm{C_{it}}(\mathrm{P_{K,it}},\mathrm{P_{L,it}},\mathrm{P_{E,it}},\mathrm{Q_{it}})=\mathrm{f}(\mathrm{A_{it}^{-1}},\mathrm{P_{K,it}},\mathrm{P_{lL,it}},\mathrm{P_{E,it}})*\mathrm{Q_{it}} \tag{1}$$

where Q is the quantity of output, P denotes price with the subscripts K, L and E representing capital, labor and energy inputs, respectively, and indexing for sector with *i* and time with *t*. The productivity term is represented by the term A, which we assume to be influenced by the level of R&D intensity (proxied by industry R&D expenditures divided by output) and capacity underutilization in each sector.

Based on Shephard's Lemma, we derive the energy factor demand function by taking the derivative of the cost function with respect to the energy price. We then have:

$$\frac{\partial C_{it}(.)}{\partial P_{E,it}}=\mathrm{E}_{it}^{d}=\frac{\partial f\,(\mathrm{A_{it}^{-1}},\mathrm{P_{K,it}},\mathrm{P_{L,it}},\mathrm{P_{E,it}})*Q_{it}}{\partial \mathrm{P_{E,it}}} \tag{3}$$

$$\frac{E_{it}^{d}}{Q_{it}}=\frac{\partial f\,(\mathrm{A_{it}^{-1}},\mathrm{P_{E,it}},\mathrm{P_{K,it}},\mathrm{P_{L,it}})}{\partial \mathrm{P_{E,it}}} \qquad (4).$$

Moving from eq. (3) to eq. (4) involves dividing both sides of eq. (3) by Q_{it} in order to get an energy intensity expression. Energy intensity is therefore a function of the productivity term and the prices of the respective input factors.

Following Metcalf (2008), we decompose energy intensity into energy efficiency and economic activity components, respectively. This is achieved by employing the so-called Fisher ideal index decomposition approach (Fisher, 1921), which is a geometric mean of the Laspeyres and Paasche indexes. A comprehensive review of index numbers and their application in the energy field can be found in Ang and Zhang (2000). Generally, aggregate energy intensity can be decomposed into activity and efficiency components as follows:

$$EI_t \equiv \frac{E_t}{Q_t} = \sum_i \left(\frac{E_{it}}{Q_{it}}\right)\left(\frac{Q_{it}}{Q_t}\right) \sum EI_{it} S_{it} \tag{5}$$

where E_t is aggregate energy use in year t, E_{it} is energy use in sector i in year t, Q_t is total output, while Q_{it} is sectoral output. Sector activity efficiency is denoted by S_{it}, and sector energy efficiency by EI_{it}. Using the Fisher ideal index approach we can construct an energy intensity index (I_{it}), which is decomposed perfectly into efficiency (I_{it}^{eff}) and activity (I_{it}^{act}) components. We have:

$$\frac{EI_{it}}{EI_{i0}} \equiv I_{it} = I_{it}^{eff} * I_{it}^{act} \tag{6}$$

EI_{i0} is energy intensity in the base year, $I_{it}^{eff} = \sqrt{LI_{it}^{eff} * PI_{it}^{eff}}$, $I_{it}^{act} = \sqrt{LI_{it}^{act} * PI_{it}^{act}}$, where LI and PI, denote the Laspeyres and the Paasche indexes, respectively, while the subscript *eff* represents efficiency and *act* denotes activity. These indexes are constructed as follows:

$$LI_{it}^{act} = \frac{\sum_i EI_{i0} S_{it}}{\sum_i EI_{i0} S_{i0}}, LI_{it}^{eff} = \frac{\sum_i EI_{it} S_{i0}}{\sum_i EI_{i0} S_{i0}}$$

$$PI_{it}^{act} = \frac{\sum_i EI_{it} S_{it}}{\sum_i EI_{it} S_{i0}}, PI_{it}^{eff} = \frac{\sum_i EI_{it} S_{it}}{\sum_i EI_{i0} S_{it}}$$

The econometric specification of the above model can in turn be expressed as;

$$\ln I_{it} = m(\ln A_{it}^{-1}, \ln P_{E,it}, \ln P_{K,it}, \ln P_{L,it}) + \varepsilon_{it} \tag{7}$$

where I_{it} is the energy intensity index constructed based on eq. (6). We log transform the variables to reduce potential outlier impacts. In eq. (7), m is an unknown function that replaces the function *f* in eq. (4). We also control for unobservables by including both time- and sector-specific dummies in eq. (4). The function *m* is assumed to be twice differentiable, and able to accommodate both discrete regressors (i.e., time and sector dummies) as well as continuous regressors (i.e., R&D intensity, capacity underutilization, the prices of energy, capital and labor inputs). Finally, ε is the random error term.

Eq. (7) is estimated using a kernel based nonparametric approach, specifically the local-linear kernel approach with mixed regressors proposed by Racine and Li (2004). The choice of this estimator relative to other kernel approaches, such as the local constant kernel estimator, is due to its ability to achieve the same rate of convergence as in a "truly" specified parametric model if the DGP is indeed linear, and also its ability to correct for boundary bias. The latter cannot be dealt with by the other kernel based estimators, especially the local constant estimator (Li and Racine, 2007).[1]

The estimation strategy is divided into three steps; in the first step the optimal bandwidth is determined for the local-linear kernel estimator implemented in estimating *m* (.) by using a least square cross-validation approach. In the second step, the optimal bandwidth found in the first step is implemented to estimate eq. (7), and in the final step, the partial regression plot and partial gradient plots for each of the regressors are obtained. In generating these plots, we implemented the "wild" bootstrap method to construct heteroskedastic consistent standard errors for the confidence bands for the partial regression and partial gradient plots.

The estimation of eq. (7) is done using the local linear kernel, with details on the estimator presented in Li and Racine (2007) to handle panel data with both continuous and discrete variables. We apply two product kernels, one for the continuous regressors and the other for the discrete regressors in the model. In this paper, the Gaussian kernel is chosen for the continuous regressors and Aitchison and Aitken (1976) is the product kernel implemented for the discrete regressors. In order to assess the efficiency and activity channels, we also estimated eq. (7) by replacing lnI with $\ln I^{eff}$ and $\ln I^{act}$, respectively.

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[1] There exist several kernel estimators and these include the local constant kernel estimator, local linear kernel estimator and local polynomial kernel estimator. See Fan and Gijbels (1996) for an in-depth treatment of local linear and polynomial kernel estimators.

The direction of the effect of relative input prices depends on the degree of substitutability between the three inputs and also on whether capital and energy are strong complements or not. For this reason, we do not a priori impose any directional restrictions on the various price effects on the energy intensity index and its components. In periods of environmental regulation stringency, e.g., due to concerns about climate change, it is expected that R&D intensity targeting environmental protection, would increase. This would have a depressing effect on energy intensity; we thus expect a negative relationship. Whether the channel of the expected negative impact of R&D on energy intensity stems from increased energy efficiency and/or changed economic activity remains an empirical question.

Energy use per output, especially in the industrial sector, depends on capacity utilization. Generally, more energy per output is needed to run production in a factory or industry operating below full capacity relative to operating at full capacity due to the fixed requirements to run the production process (Bernstein et al., 2003). This is true for new plants and machines but not necessarily for older plants and machines, whose energy use per output may increase as capacity utilization approaches full capacity. Still, overall we hypothesize that capacity underutilization should be positively related to energy intensity.

Given eq. (7), we can now also empirically address the issue of convergence in energy intensity across the different manufacturing sectors. The observed differences could be converging or diverging depending on the processes that govern the development. For instance, the energy intensities could be converging due to factor price equalization or diminishing returns to capital accumulation, as well as following technology transfer and knowledge spillovers between firms and across sectors. The observed differences in energy intensity could also diverge as a result of learning effects, increasing returns to capital accumulation due to externalities and market imperfections and specialization that could result in multiple steady states and different paths of capital accumulation (Grossman and Helpman, 1991). However, since energy is an intermediate input in the production process and not a joint product of output, there is little reason to believe that diminishing returns to capital should be an important source of energy productivity/energy intensity convergence, at least as long energy and capital are not strongly complementary (Mulder and De Groot, 2007).

Our energy convergence analysis is based on the beta convergence concept, which is firmly rooted in neoclassical growth theory (Solow, 1956; Swan, 1956; Brock and Taylor, 2004). For our purposes this implies that high energy intensity sectors should experience higher relative declines in energy intensity compared to sectors with already relatively low energy intensities. The implication is that sectors with higher initial level of energy intensity will "catch-up" with the lower-energy intensity sectors.[2]

Based on eq. (7) and the neoclassical growth theory framework our energy intensity convergence model specification takes the following form:[3]

$$\ln(\mathrm{I}_{\mathrm{it}} - \mathrm{I}_{\mathrm{it\text{-}3}}) = m(\ln\mathrm{I}_{\mathrm{it\text{-}3}}, \ln\mathrm{A}^{-1}_{\mathrm{it}}, \ln \mathrm{P}_{\mathrm{E,it}}, \ln \mathrm{P}_{\mathrm{K,it}}, \ln \mathrm{P}_{\mathrm{L,it}}) + v_{\mathrm{it}} \tag{8}$$

Our variable of interest is the initial level of energy intensity, i.e., $\ln\mathrm{I}_{\mathrm{it\text{-}3}}$, and its relationship with the three-year average growth in energy intensity, $\ln(\mathrm{I}_{\mathrm{it}}\text{-}\mathrm{I}_{\mathrm{it\text{-}3}})$, to test for the energy intensity convergence hypothesis. The test for conditional beta convergence is based on the sign and statistical significance of the relationship between the growth in energy intensity and the initial level of energy intensity. There is evidence of convergence if this relationship is negative and statistically significant, divergence if it is positive and significant, and no evidence of both convergence and divergence if it is not statistically significantly different. We used three-year averages in order to reduce cyclical impacts as is commonly done in the growth literature (e.g., Barro, 1997; Bassanini and Scarpetta, 2001; Islam, 2005). In the growth literature, five-year averages are generally preferred because it is the minimum period required to completely wipe out cyclical effects at the macroeconomy level. We choose three-year averages instead because we want to maintain a reasonable sample size for the non-parametric estimation.

3. Data definition and sources

The data for this study is a unique and detailed panel data set for the Swedish industry covering the period 1990 to 2008 for 14 Swedish manufacturing sectors (SNI10-SNI37)

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[2] There are other concepts in the convergence literature; these include sigma (σ) and stochastic convergence. Sigma convergence refers to a decrease in variance in cross country (or sector) differences in energy intensity levels, while stochastic convergence refers to whether shocks to energy intensity for one country (or sector) relative to another (or the average of the sample) are temporary (see Pettersson et al., 2014, for a recent review on convergence and the various concepts applied to carbon dioxide emissions).

[3] In the literature, beta convergence is classified into two- unconditional (absolute) and conditional (relative) beta convergence. The difference between the two is that absolute convergence implies that all sectors exhibit the same growth path and stead-state level of energy intensity, while relative convergence means that the growth paths differ and therefore all sectors do not converge to the same steady state. Since we control for, for instance, time-specific and sector-specific effects, we test for conditional beta convergence.

provided by Statistics Sweden. This data set is unique in the sense it contains detailed information on economic variables for each of the 14 industry sectors, energy use and costs, R&D expenditures, the rental price of capital, wage bills, number of employees, wages, emissions and environmental taxes such the carbon dioxide tax. Brännlund and Lundgren (2010, 2007), Brännlund et al. (2014), Brännlund et al. (2015), Färe et al. (2014), are some of the works that have utilized this data set, and in which the reliability and quality of the data set have been well documented. Each of the previous work used a subset of variables in this data set to address their respective research question(s).

In this study we use data on energy use (quantity in terms of megawatt hours (MWh) of fossil fuel, electricity, biofuel and district heating), output (value of sales divided by a sector-specific producer price index), R&D intensity (environmental protection R&D cost divided by output), energy price (i.e., a weighted average price of all used energy including biofuel and electricity), rental price of capital and wages (labor cost/employees). Moreover, we used data such as energy and output to construct energy intensity index, I_{it} (constructed based on the Fisher ideal index). We also used data on output to construct a proxy for capacity underutilization, here defined as the log ratio of potential output over output, similar to Bernstein et al (2003). The potential output was created via the Hodrick–Prescott filter. All price variables were converted into real terms using the producer price index (PPI).

Table 1 presents the descriptive statistics for the key variables used in the analysis, and for all of the 14 industrial sectors. The descriptive statistics reveal significant variation in the key variables in the data set, particularly, output, energy use, prices and the energy intensity index. The pulp and paper sector has experienced the most variation in energy use among the 14 industry sectors, while the textile sector has had the smallest standard deviation in terms of both quantity of energy used and the variation within the sector over time. The other leading users of energy inputs are the basic iron and steel and the chemical sectors, both having average energy use levels well above the average for the total industry.

The basic iron and steel sector is the most energy intensive sector based on the mean value and also the most volatile sector (i.e., it has the highest standard deviation in terms of energy intensity), while on the average, the electronic sector is the least energy intensive sector in Sweden over the period covered. The price of energy also varies across sectors with basic iron and steel sector having the lowest energy price (0.10 SEK/Kwh), while the electronics sector has the highest energy price (0.36 SEK/Kwh). The mean monthly wages in the chemical sector (41846 SEK per month) are the highest, followed by the electronics sector (37869 SEK per month), with averages above the mean wage of total industrial sector (32410 SEK per month).

Table 1: Descriptive statistics (mean and standard deviation)

Manufacturing sectors	Output MSEK	Energy MWh	P_E SEK/kWh	P_L SEK/Month	P_K	I	I^{eff}	I^{act}
Basic iron & steel	32974	17400000	0.10	33027	0.14	3.83	3.47	1.05
	9956	**8412933**	**0.02**	**7470**	**0.06**	**1.85**	**0.94**	**0.32**
Chemical	50191	7097182	0.13	41846	0.13	1.57	1.00	1.58
	17293	**2779078**	**0.06**	**12864**	**0.05**	**0.61**	**0.21**	**0.54**
Electronic	101588	780674	0.36	37869	0.18	0.65	0.44	2.31
	64139	**154242**	**0.26**	**12365**	**0.03**	**0.13**	**0.30**	**1.46**
Fabricated metal	10229	502300	0.24	28639	0.13	1.22	0.91	1.41
	3435	**248413**	**0.09**	**5877**	**0.05**	**0.61**	**0.35**	**0.47**
Food	89339	5060266	0.27	29974	0.15	0.94	0.90	1.04
	4525	**404392**	**0.12**	**7518**	**0.04**	**0.07**	**0.09**	**0.05**
Machinery	69622	1965207	0.21	32404	0.13	1.04	0.95	1.14
	18361	**273943**	**0.09**	**7848**	**0.04**	**0.14**	**0.22**	**0.30**
Mining	11156	4271676	0.13	36231	0.14	1.34	1.17	1.14
	1641	**905942**	**0.05**	**9566**	**0.06**	**0.28**	**0.18**	**0.17**
Motor vehicle	135385	2582978	0.21	33599	0.14	0.94	0.60	1.76
	53975	**329108**	**0.10**	**8416**	**0.04**	**0.12**	**0.19**	**0.70**
Printing	5295	263221	0.19	31164	0.12	1.51	1.50	1.08
	2540	**69690**	**0.08**	**6206**	**0.05**	**0.40**	**0.37**	**0.52**
Pulp and Paper	77099	30900000	0.14	34490	0.15	1.40	1.30	1.06
	10062	**8658748**	**0.07**	**8332**	**0.05**	**0.39**	**0.24**	**0.14**
Rubber and Plastic	12550	823879	0.24	29624	0.14	1.12	1.23	0.91
	2005	**200315**	**0.11**	**6740**	**0.05**	**0.27**	**0.23**	**0.14**
Stone and Mineral	15626	4756468	0.14	30325	0.13	0.75	0.91	0.84
	2779	**573687**	**0.04**	**7085**	**0.05**	**0.09**	**0.13**	**0.15**
Textile	5038	563765	0.27	26504	0.14	0.85	1.31	0.65
	1188	**151005**	**0.13**	**6838**	**0.04**	**0.23**	**0.25**	**0.15**
Wood	36721	4734789	0.12	28038	0.17	2.60	1.59	1.53
	11908	**2417926**	**0.03**	**5820**	**0.04**	**1.33**	**0.49**	**0.49**
Total	46629	5831006	0.20	32410	0.14	1.41	1.24	1.25
	46576	**8808154**	**0.13**	**9078**	**0.05**	**1.05**	**0.78**	**0.67**

Note: Bold values are standard deviations. The total number of observations is 266, 19 for each sector.

4. Results

This section consists of two main parts. In the first part (sections 4.1-4.2) we present the estimates for the determinants of energy intensity and provide a brief discussion on the channels of these factors on energy intensity. Thus, the latter addresses to what extent the results can be attributed to changes in energy efficiency and/or changes in the level of economic activity. The second part (sections 4.3-4.4) presents and discusses the results concerning conditional beta convergence, and the extent to which this can be attributed to efficiency or activity changes.

4.1 Determinants of energy intensity

We estimated eq. (7) by applying a full nonparametric model. The summary results of the estimated model in terms of regression type, method used for the selection of bandwidth and the adjusted R square are reported in Table A1 in the appendix, while the estimated regression lines are presented in Figure 1. These results reveal the following:

(a) The energy price has had a negative but linear impact on industrial energy intensity. The negative relationship between energy price and energy intensity could be due to factor substitution and/or an inefficient use of energy. First, as the price of energy increases, firms may substitute capital and labor for the energy input, thus reducing energy intensity. Second, firms may use energy inefficiently (e.g., due to information asymmetries, split incentives etc.) but as energy prices increase they become more attentive to eventual inefficiencies and decrease energy use (e.g., Mansikkasalo, 2013). These results are in line with the findings from Metcalf (2008) for the U.S., utilizing state-level data.

(b) Energy intensity is negatively related to the price of capital and this relationship is also linear. The implication is that as the price of capital increases, firms are likely to reduce the capital input and replace that with labor. If most of the capital replaced requires significant energy services to operate (as is often the case in industrial sectors), energy intensity will decrease with a decrease in capital use, thus leading to a negative relationship between energy intensity and price of capital.

(c) The price of labor is positively related to energy intensity, thus suggesting that as price of labor become expensive, firms are likely to substitute capital and energy for labor thus increasing energy intensity in the process.

(d) The estimated relationship between energy intensity and R&D intensity is constant, in turn suggesting an insignificant effect of R&D intensity on energy intensity. A possible explanation for this result is that it takes time before R&D activities result in new and applicable technologies and processes, and all R&D activities do not necessarily generate any valuable results. Therefore there is a significant time lag between R&D expenditures and their effect on the input mix in the production process. A second plausible reason is that R&D activities may have opposing effects on the efficiency and activity components of energy intensity. This is because the efficiency component is expected to increase with R&D activities, especially those activities that result in efficient use of energy and capital inputs. This however will have a negative effect through the activity channel since R&D intensity may result in less energy intensive economic activity, thus resulting in a negative association between the activity component and R&D activities.

(e) Finally, the results indicate a positive relationship between energy intensity and capacity underutilization. However, the slope is almost flat, suggesting a rather small positive effect of capacity underutilization. The positive effect supports the hypothesis that more energy per output is needed to run production in a factory or industry operating below full capacity than at full capacity due to the fixed requirements to run a production process. However, the relatively flat slope could be due to opposing effects from the two components of energy intensity (efficiency versus activity), which reduce the combined effect on energy intensity.

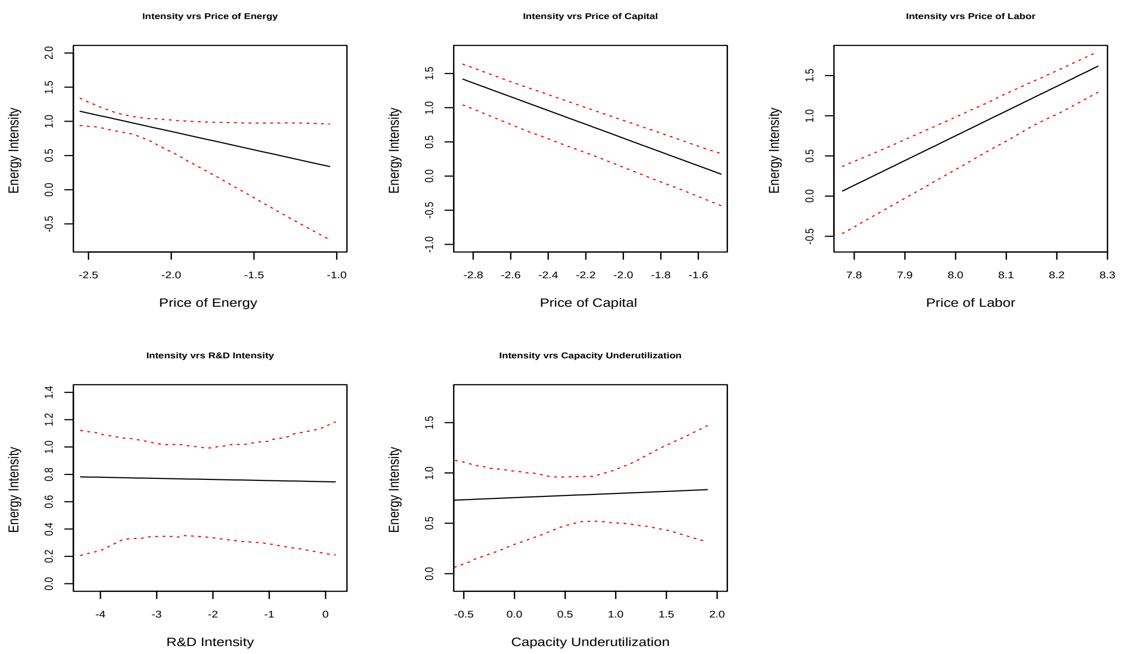

Figure 1: Partial nonparametric regression plot of energy intensity verses its determinants

Notes: The solid lines are the nonparametric fit and the dashed lines are "wild" bootstrap standard errors. Y-axis is energy intensity (in logs) and X-axis corresponds to each determinant as specified in the model presented in eq. (7). Both time and sector dummies were included in the estimations but reported.

4.2 Decomposing energy intensity into efficiency and activity effects

In this sub-section we look at the channels of the effects by evaluating the gradients of each of the estimated functions between energy intensity and the determinants as well as between its components and the determinants. The result from this exercise is reported in Figure 2; the estimated regression lines for efficiency and activity indexes are reported in appendix A2. The results reveal that the price effects predominantly originate from the efficiency channel. This conclusion is due to the fact that the estimated gradient values of each of the price variables from the efficiency model are larger in absolute terms relative to those from the activity model. In addition, the price estimates from the efficiency model have the same sign as the estimates from the efficiency model, which is not the case for the estimates from the activity model. For instance the estimated energy price elasticity from the energy intensity model is about -0.5, while the elasticities from the efficiency and activity models are about -0.5 and 0.1, respectively.

In the case of the price of capital, the elasticity from energy intensity, efficiency and activity models are -1.0, -0.6 and -0.4, respectively, also indicating a significant influence from the efficiency channel over the activity channel. Nevertheless, the influence from the activity channel is statistically significant, and therefore reinforces the effect from the efficiency channel.

Given that the estimated function between energy intensity and R&D intensity is linear with a constant slope (see Figure 1), we expected a zero gradient line between energy intensity and R&D intensity. The results reported in Figure 2 confirm this, thus suggesting an insignificant (in terms of magnitude) effect of R&D intensity on energy intensity. However, the gradient plots from the efficiency and activity models suggest that the insignificant impact can be attributed to both channels, this since their respective values are the same but with opposite sign (i.e., about 1 and -1 from the efficiency model and the activity model, respectively). The estimated elasticity for capacity underutilization is approximately 0.05, and this stems from both the efficiency and the activity channel; the estimated effect from the efficiency model range from -0.5 to 1, while from the activity model it ranges from -0.2 to 0.2.

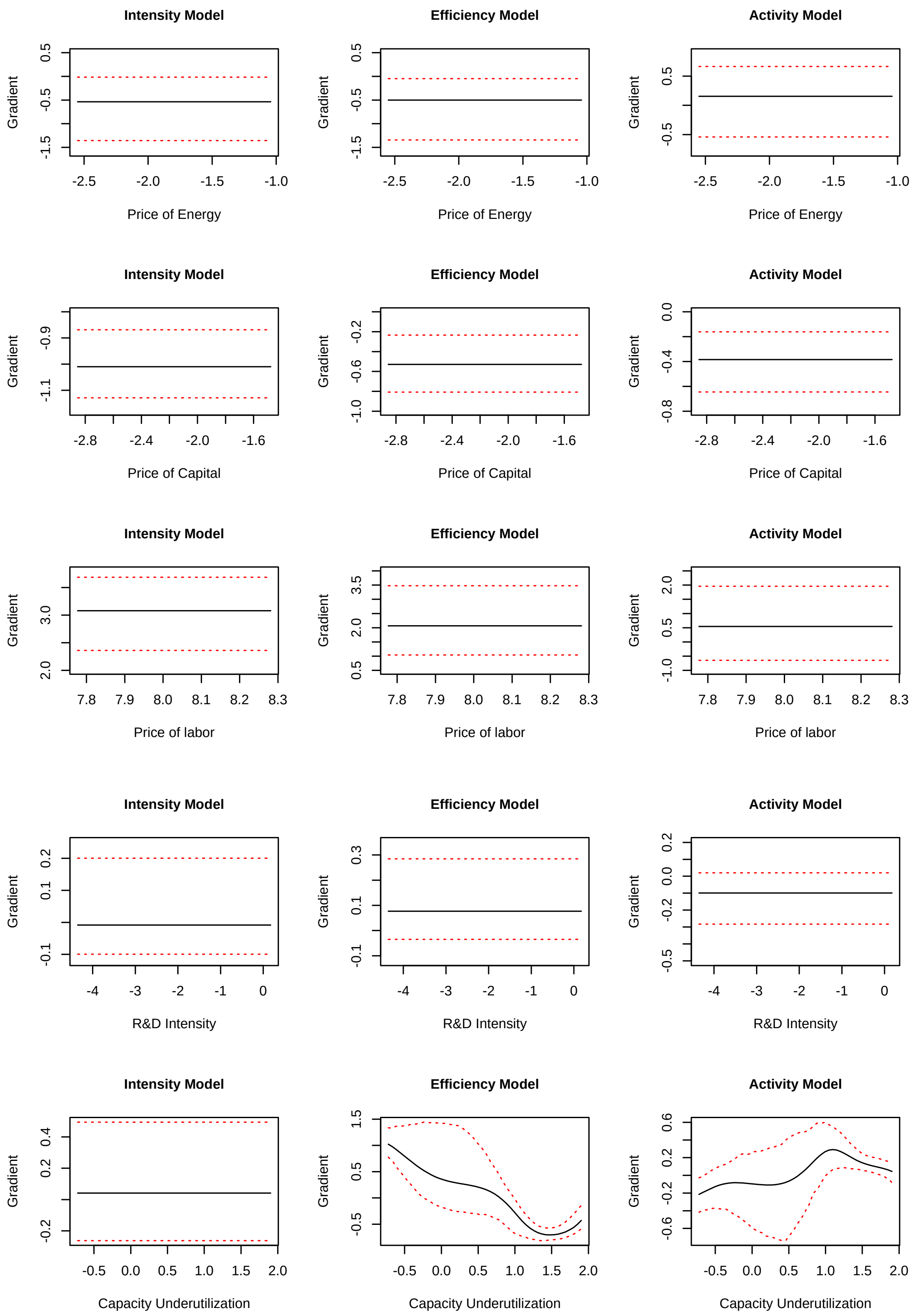

Figure 2: Nonparametric Gradient plot of the determinants of energy intensity.

Notes: The solid lines are the nonparametric gradient line and the dashed lines are "wild" bootstrap standard errors. The gradient is estimated as $\partial\hat{m}(x_{it}, \bar{x}_{i-1,t}) / \partial x_{it}$ *, where* x_{it} *is the variable of interest and* $\bar{x}_{i-1,t}$ *is all other variables held at their mean.*

4.3 Convergence in energy intensity

In this sub-section we present the conditional beta convergence estimates based on the specification in eq. (8). The estimated regression lines are reported in Figure 3, and reveal a negative relationship between growth in energy intensity and lagged energy intensity (i.e., the initial level of energy intensity). This suggests thus that energy intensity converges (conditionally) for the 14 different industrial sectors in Sweden. The estimated function is linear, implying that the rate of convergence, which in this case is the gradient of the estimated function, is constant. This means that the rate of convergence in energy intensity to the respective steady states in Swedish industrial sectors cannot be assumed to vary with the level of energy intensity for the period covered by the data.

The estimated energy price function is linear but with a negative slope implying an inverse relationship between the growth rate of energy intensity and energy price. This relationship could be explained by the substitution between the inputs, thus as the price of energy increases, firms are likely to substitute labor for both capital and the energy input, and in the process reduce the growth rate of energy intensity. A second explanation could be that the high energy prices induce firms to be more efficient in their use of energy in the production process, thus reducing the growth rate in energy intensity.

The estimated functions for both the price of capital and labor are linear but flat, implying that both variables have insignificant (in terms of magnitude) effects on energy intensity. A possible explanation for this is that firms tend to substitute between capital and labor relative to their prices in a way that ensures at least producing the same level of output before the price changes. The implication is that the growth dynamics of the substitution effect between capital and labor would be insignificant, thus the almost flat slopes for both capital and labor prices on the growth rate of energy intensity.

We also found a linear but negative function for R&D intensity and the growth in energy intensity. The explanation for this inverse relationship likely stems from the ability to successfully transform R&D activities into new technologies and processes that result in a more efficient combination of inputs to produce a given output and therefore reduce input requirements (including energy) in the production process. The associated new processes and technology would result in more output per input combination, which in turn results in less growth in energy intensity.

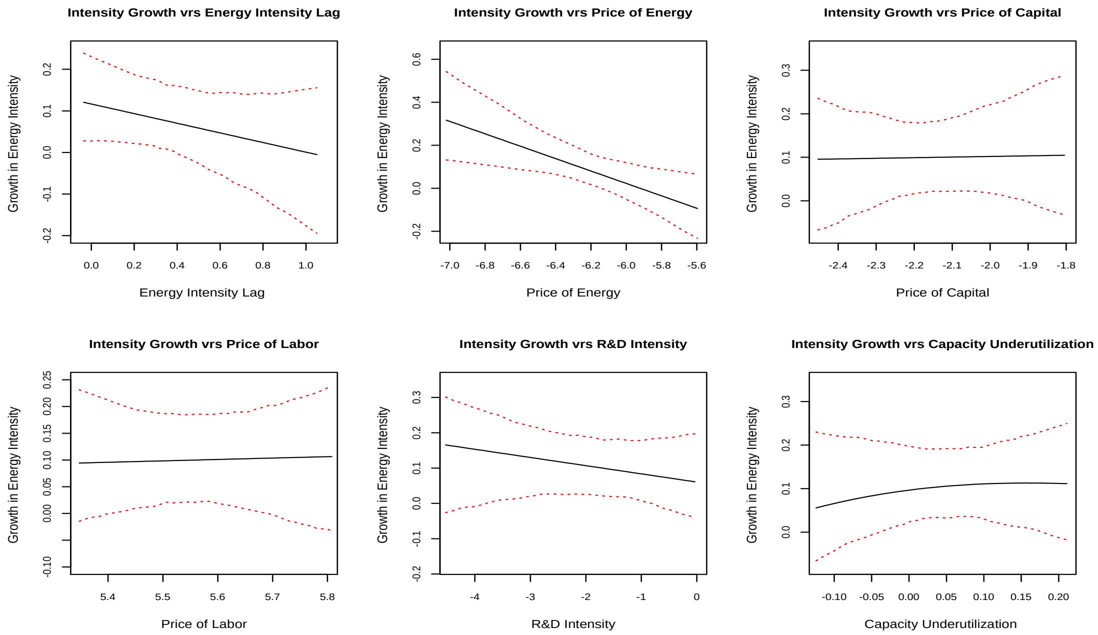

Figure 3: Partial nonparametric regression plot of growth in energy intensity verses initial level of energy intensity, factor prices, R&D intensity and capacity underutilization.

Notes: The solid lines are the nonparametric fit and the dashed lines are "wild" bootstrap standard errors. Y-axis is energy intensity (in logs) and X-axis corresponds to each determinant as specified in the model presented in eq.(7). Both time and sector dummies were included in the estimations but reported.

Furthermore, the results indicate a positive impact of capacity underutilization that tends to vary slightly over different levels of capacity underutilization. The reason for this relationship is that there is a fixed energy requirement in keeping production running, and this means that producing at full capacity or close to full capacity would likely result in more output per energy relative to operating below capacity. Therefore the growth in energy intensity at a low level of capacity utilization, in general would be higher than the growth rate at high level of capacity utilization. As the capacity utilization rate get close to full capacity, the growth rate in energy intensity would decline towards zero and may turn negative at full capacity.

4.4 Efficiency and activity channels of energy intensity convergence

The channels of energy intensity convergence can be assessed by looking at the gradient plot of the growth in energy intensity and lagged energy intensity, and by comparing the resultant gradient value(s) to those from the components of energy intensity index (efficiency and activity components). Figure 4 presents the gradient plots for lagged energy intensity from the energy intensity, efficiency and activity models, respectively (the estimated regression lines for efficiency and activity indexes are reported in appendix A3). The gradient values reveal that the beta convergence in energy intensity stems from the activity channel rather than from efficiency channel. A plausible explanation for this result is that Swedish industry has experienced structural changes that have promoted energy intensity convergence across sectors. Part of this could be related to leakage of energy intensive production (e.g., newsprint mills) to other countries while instead re-importing energy-intensive goods.

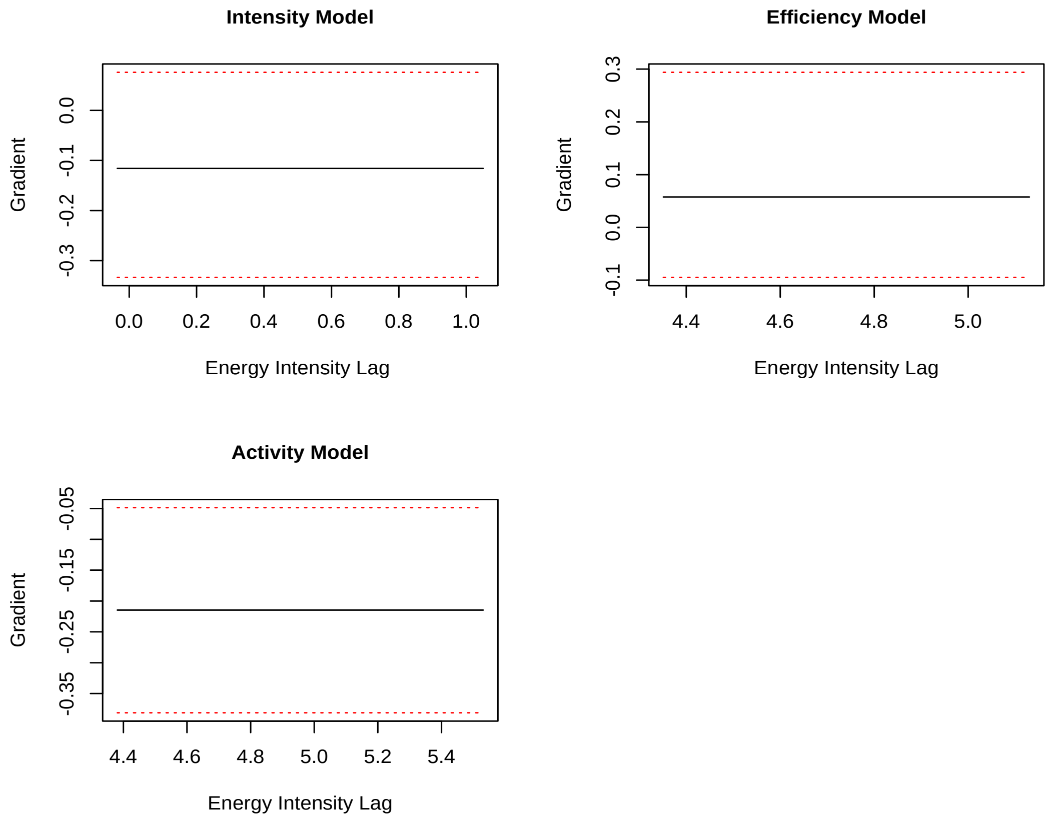

Figure 4: Nonparametric Gradient plot of conditional beta convergence in energy intensity and its components (efficiency and activity).

Notes: The solid lines are the nonparametric gradient line and the dashed lines are "wild" bootstrap standard errors. The gradient is estimated as $\partial\hat{m}(x_{it}, \overline{x}_{i-1,t}) / \partial x_{it}$*, where* x_{it} *is the variable of interest and* $\overline{x}_{i-1,t}$ *is all other variables held at their mean*

The above effect could also generate structural shifts in terms of inter and intra-industry job turnover resulting in differences in capital intensity across different manufacturing sectors and as a consequence result in convergence in energy intensity. The evidence of a composition effect in Swedish industries via job turnover can be found in Andersson

(2000). They found the rate of inter-industry job turnovers in Swedish manufacturing to be driven by differences in profits, which, shifts in international competitiveness play a crucial role. Other studies such as Kander and Lindmark (2004) found significant structural shifts in explaining Swedish energy intensity trend within the industrial sector but no aggregate energy intensity trend. This is consistent with our findings.

Our finding regarding the channel of convergence in energy intensity is contrary to that found by Mulder and de Groot (2012) for cross-country sector level convergence across OECD countries. They found convergence in energy intensity to stem from the efficiency channel. This difference in results can be explained by whether the convergence is tested across countries or across sectors within a country. It is reasonable to expect technological transfers across countries for the same industry. However, the limited influence of the efficiency channel in our case indicates that it is difficult to promote the transfer of energy efficient technology across sectors with very different productions processes.

5. Conclusion

The objective of this study was to provide a more in-depth understanding of industry sector differences in energy intensity and their determinants, and to test for convergence to understand if backward sectors have been catching up with leading sector in terms of energy intensity. Moreover, we were not only interested in testing the convergence hypothesis, but also in elaborating on the channels of convergence and the drivers of energy intensity, i.e., the extent to which they can be attributed to changes in energy efficiency and/or in economic activity. In addressing our objective, we utilized a unique sector level panel data and a reduced-form model, focusing on 14 Swedish industry sectors for the period 1990-2008. The model was derived from production theory; we also employed the Fisher ideal index technique to construct an energy intensity index, which can be perfectly decomposed into efficiency (technique) and activity (composition) components and used separately as the dependent variable for the non-parametric regression analysis.

Interesting findings emerged from the analysis. First, from the energy intensity determinant model, input prices were shown to have had more profound effects (in terms of the absolute magnitudes of the elasticity values) on industrial energy intensity than R&D intensity and capacity underutilization. This suggests among other things that factor input mixes have played significant roles as drivers of energy intensity in Swedish industrial sectors relative to both R&D intensity and capacity underutilization. The insignificant impact of R&D intensity could be attributed to the relatively long period required for R&D expenditures to generate successful new technologies and processes. Moreover, we found that the channel of each of the price effects on energy intensity primarily stemmed from the efficiency channel. In the case of R&D intensity and capacity underutilization, the effects stemmed from both the efficiency and the activity channels.

Second, we found evidence of beta convergence in energy intensity across Swedish industry sectors, and that this primarily could be attributed to the activity channel. The efficiency channel had a positive effect, thus suggesting energy divergence in efficiency, though the rate of the divergence parameter was rather small (0.05) relative to the convergence parameter (-0.2) from the activity component. This finding implies that during the studied time period, Swedish industry shifted away from more to less energy-intensive production, in part perhaps driven by moving energy-intensive manufacturing abroad.

The results further revealed that in the convergence model, among the input prices, only the price of energy had a significant (in terms of magnitude) impact on the growth rate of energy intensity. The prices of capital and labor instead had insignificant effects on the growth rate of energy intensity. Higher prices of energy tend to trigger more energy efficiency or substitution into other inputs and this increases the negative effect of energy prices on the growth rate of energy intensity. In principle this means that higher taxes on energy is a potential option for policy makers to induce energy intensity reduction within the Swedish industrial sector, at least if the taxes are well designed to avoid unintended outcomes such as being too high and inducing firms to move part of their production elsewhere.

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Appendix

Table A1:

Nonparametric panel regression of the determinants of energy intensity

Regressors	Intensity	Efficiency	Activity
Log energy price	…	…	…
Log capital price	…	…	…
Log labor price	…	…	…
Log R&D intensity	…	…	…
Log capacity underutilization	…	…	…
Time dummies	…	…	…
Sector dummies	…	…	…
Adjusted R-Square	0.95	0.97	0.97
Number of Observation	266	266	266
Regression Type: Local-Linear			
Bandwidth Selection Method: Least Squares Cross-Validation			

Nonparametric panel regression of energy intensity convergence model

Regressors	Intensity	Efficiency	Activity
Log energy intensity (lagged)	…	…	…
Log energy price			
Log capital price	…	…	…
Log labor price	…	…	…
Log R&D intensity	…	…	…
Log capacity underutilization	…	…	…
Time dummies	…	…	…
Sector dummies	…	…	…
Adjusted R-Square	0.50	0.66	0.50
Number of Observation	70	70	70
Regression Type: Local-Linear			
Bandwidth Selection Method: Least Squares Cross-Validation			

Note:

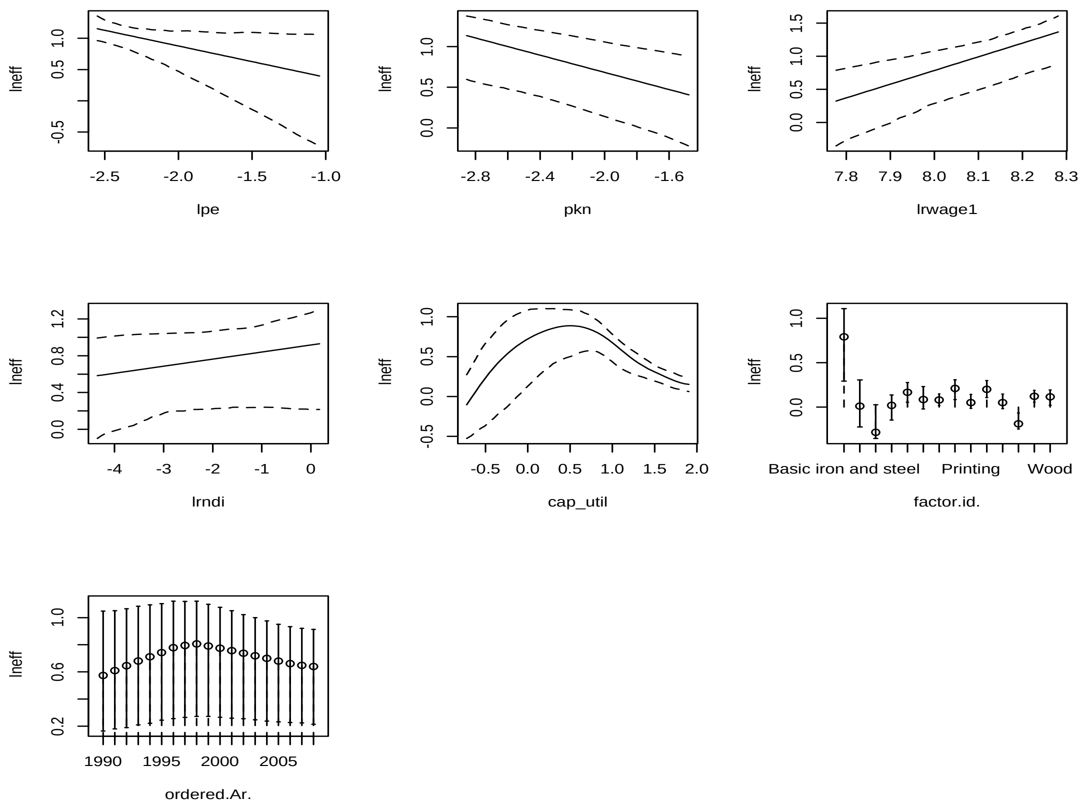
... indicates that the varible is estimated by nonparametric model.

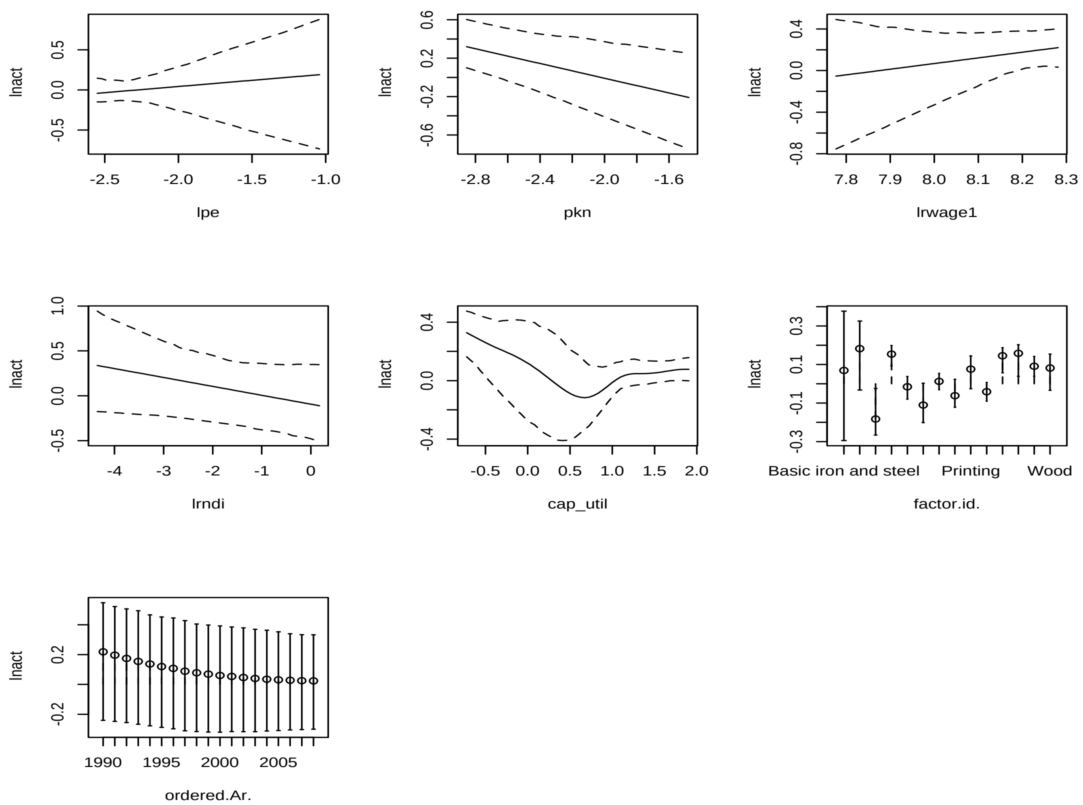
Intensity denote the use of energy intensity as the dependent variable

Efficiency denote the use of efficiency index as the dependent variable

Activity denote the use of activity index as the dependent variable.

Appendix A2: Efficiency and activity determinants model





Note:

Lneff denote log energy efficiency index.

Lnact denote log activity index.

Lpe denote log energy price.

Pkn denote log capital price.

Lrwage1 is log price of labor.

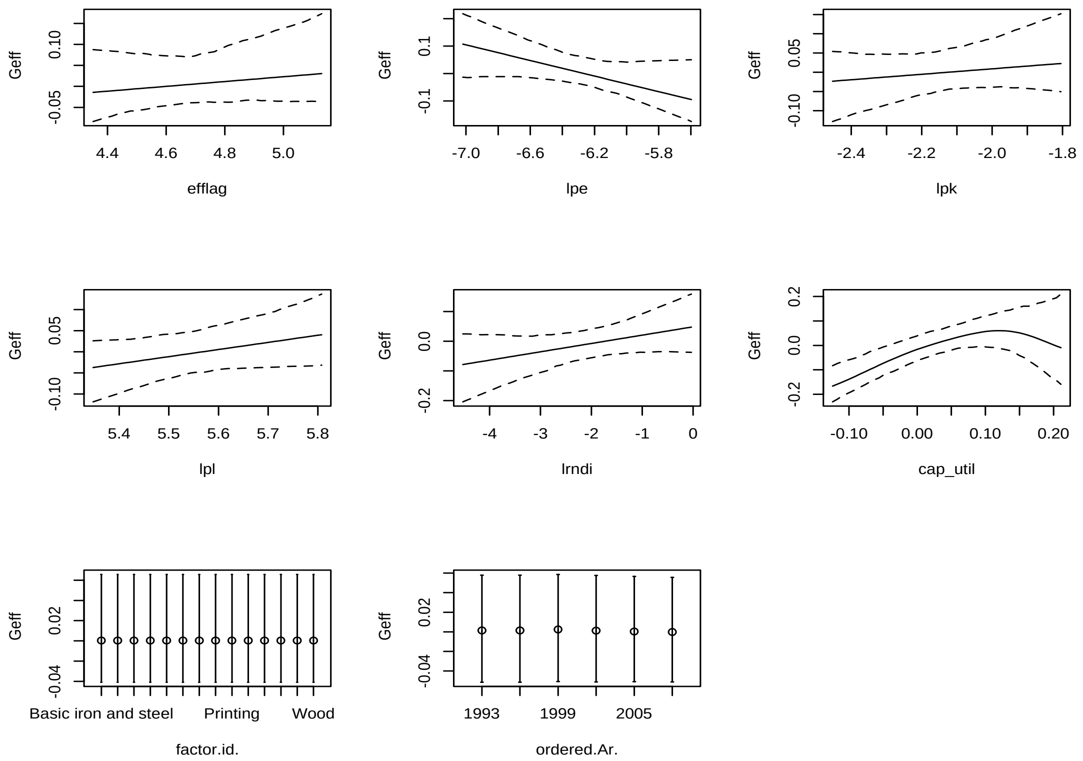
Lnrndi is log R&D intensity.

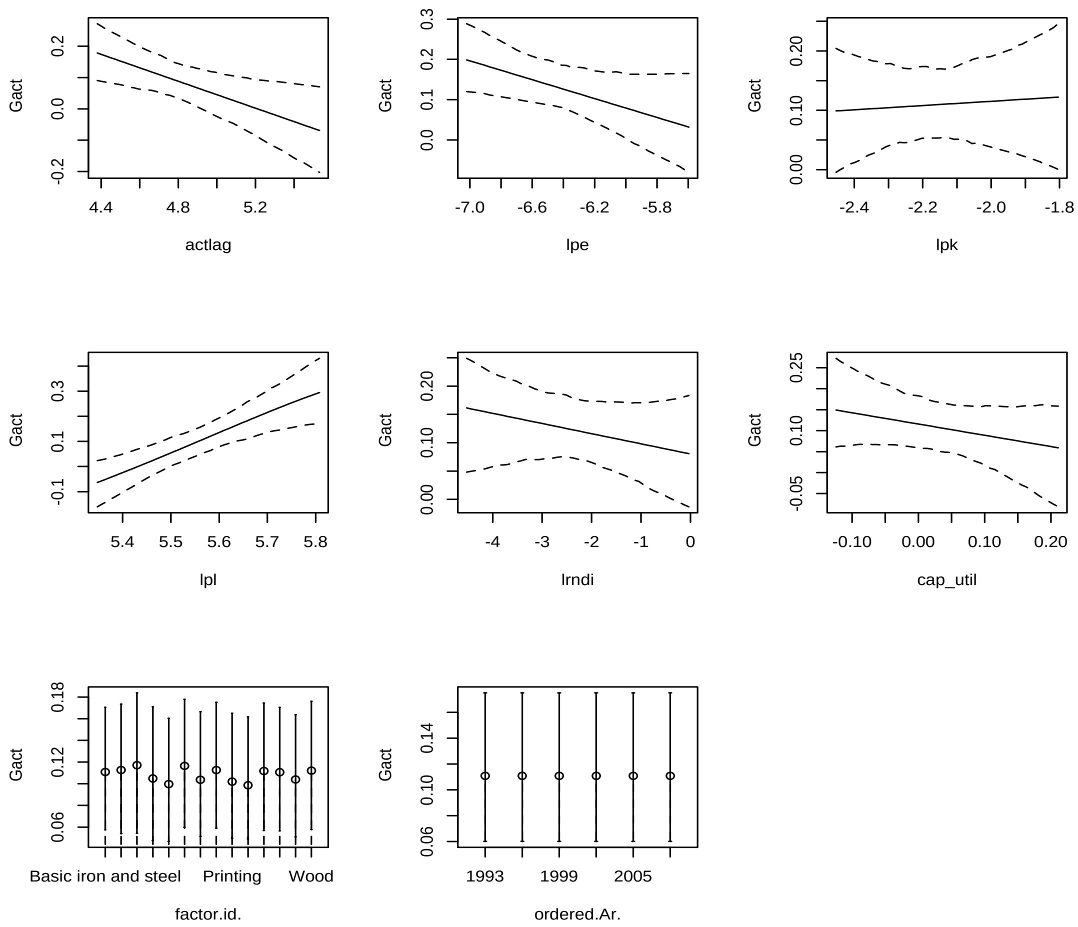
Cap_util represents capacity underutilization.

Factor.id demote sector dummies.

Ordered.Ar denotes time dummies.

Appendix A3 : Efficiency and activity convergence models





Note:

Geff denote growth in energy efficiency index.

Gact denote growth in activity index.

Efflag represents lagged log energy efficiency index (initial energy efficiency)

Actlag denotes lagged log activity index (initial activity)

Lpe denote log energy price.

Pkn denote log capital price.

Lrwage1 is log price of labor.

Lnrndi is log R&D intensity.

Cap_util represents capacity underutilization.

Factor.id demote sector dummies.

Ordered.Ar denotes time dummies.