

Convergence of carbon dioxide performance across Swedish industrial sectors

An environmental index approach

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Abstract

The overall objective of the paper is to analyze convergence of CO₂ emission intensity across manufacturing sectors in Sweden. Our approach differs from previous work on carbon convergence in that it employs a theoretical framework to construct a CO₂ performance index, which explicitly takes into account that industrial firms produce good as well as bad outputs. This index is then used as the dependent variable in a growth-type regression equation. We employ a data set covering 14 industrial sectors over the time period 1990-2008. The results suggest the presence of conditional β -convergence in CO₂ performance among the industrial sectors in Sweden. Moreover, the speed of convergence varies significantly in the sense that the higher the capital intensity is, the lower is the convergence rate to the different steady states. This reflects the importance of – and in part the costs associated with – capital turnover to achieve a transition towards lower CO₂ emission paths.

Key words: convergence; carbon dioxide emission intensity; industry; Sweden

1. Introduction

The objective of this paper is to empirically analyze carbon dioxide (CO₂) emission intensity convergence across manufacturing sectors in Sweden. The novelty here is basically that our approach has a natural underpinning based on production theory. As such it differs from the traditional environmental, or emission, convergence literature in the sense that it studies the growth path of the (inverse) emission intensity. An important advantage with this approach is that it takes explicit account of the notion that firms produce good and bad outputs simultaneously¹ This is in contrast to the more commonly used growth-path of emission approach, which ignores this multi-output property and, for instance, regresses the growth rate of CO₂ emissions per capita on the initial (or lagged) level of emission per capita and the gross domestic product (GDP) (Pettersson et al., 2014).

Our empirical methodology can be described as a straightforward two-step approach; in the first step we calculate an environmental (CO₂) performance index for each industrial sector in each year. In the second step we employ this index as the dependent variable in a growth-type regression equation.

The motivation for studying CO₂ emissions convergence between sectors within a country is two-fold. First, it will provide knowledge of what we can expect concerning future convergence at the global level. For instance, if different industry sectors are found to converge (conditionally) towards different steady-state levels, this would imply that countries with similar industry structures are more likely to converge, while the opposite would hold for countries with different industrial composition. This may have possible repercussions for the perceived fairness of different global climate policy burden-sharing schemes (see also section 2). Moreover, since panel data usually are more detailed and reliable on the country level than aggregate data across countries, a within-country analysis may in many cases be preferable. Second, a within-country analysis could be important and interesting on its own, especially concerning the consequences for different sectors of climate and energy policies. For instance, it may provide a possibility to study distributional issues, or burden sharing, within a country as a result of a global or national policy.

¹ Miketa and Mulder (2005), Mulder and de Groot (2012) and Liddle (2009) analyze energy productivity and intensity (including convergence patterns). Moutinho et al. (2014) also address convergence of CO₂ intensity across different energy and industrial sectors (in Portugal). However, none of these studies provide the theoretical underpinnings and relate to these in the empirical analyses.

The case in our study is Sweden. The reason for this is also two-fold. Firstly, we have access to a unique and detailed panel data set for the Swedish industry, which facilitates an in-depth analysis of this kind. Specifically, we employ data across 14 industrial sectors over the time period 1990-2008. Secondly, Sweden has since a fairly long time had a very active climate and energy policy, including significant changes in carbon and energy taxes over time. The Swedish CO₂ tax (including some deductions for energy-intensive industrial sectors) was introduced already in 1991. This makes it interesting to analyze emission dynamics in Swedish industry sectors, and to relate it to changes in fuel prices, capital intensity, etc.

Finally, since we in this study have data on capital intensity for the different sectors it can also be viewed as a micro-level illustration of the role of capital turnover in the transition towards lower emissions, which is of great relevance also in a global context.

The remainder of the paper is structured as follows. In the next section we give a more detailed background and a view of the literature within the area of convergence of CO₂ emissions. In section 3 we go through the basic theoretical framework of our approach, whereas the empirical model and method are outlined in section 4. The data we use in the study are presented and discussed in section 5, and the results from the analysis in section 6. Finally, section 7 is devoted to some concluding comments.

2. Background to the CO₂ convergence literature

Over the last few decades a rich empirical literature investigating convergence of CO₂ emissions among countries worldwide has emerged (see Pettersson et al., 2014 for a recent review). This research has been particularly devoted to the issue of convergence per capita emissions. An important reason for this focus is that convergence in per capita terms could influence the political economy of negotiating multilateral climate agreements (e.g., Aldy, 2006). Allocating to each individual the same “right to pollute” tends to appeal to many on grounds of fairness, and this principle has been endorsed by a number of national governments (typically in developing countries), non-governmental organizations and scholars (e.g., Frankel, 2007; Mattoo and Subramanian, 2010). However, if per capita emissions cannot be expected to converge, such an allocation principle would result in substantial international transfers of rents through carbon allowance trading or the relocation of emissions-intensive industries. If, on the other hand, per capita CO₂ emissions converge across countries and over time, this concern would be less important and additional countries

(i.e., also intensive emitters in the developed world) could be more likely to endorse the per capita principle.

Methodologically, the empirical carbon convergence research can roughly be divided into three different concepts: beta (β), sigma (σ) and stochastic convergence. These can in turn be divided into conditional (relative) and unconditional (absolute) convergence. β -convergence follows from the neoclassical economic growth literature (e.g., Solow, 1956), and implies that countries with lower initial emission levels will experience higher emissions growth levels and hence “catch-up” with the higher-emission countries. Moreover, absolute β -convergence implies that all countries exhibit the same steady-state level of emissions, while the relative counterpart means that the growth paths differ and thus do not converge to the same level. β -convergence of CO₂ emissions has been addressed in a few previous studies (e.g., Strazicich and List, 2003; Van Nguyen, 2005; Brock and Taylor, 2010). Over time, though, increased attention has also been devoted to other convergence concepts such as so-called σ -convergence, which translates into a decrease over time in the cross-section variance of per capita emissions (e.g., Aldy 2006; Panopoulou and Pantelidis, 2009; Camarero et al., 2013). This approach has led to the use of more rigorous non-parametric testing procedures taking into account the dynamics of the full distribution of countries, and thus not only the conditional mean (β -convergence) or the variance (σ -convergence). The distributional dynamics approach follows Quah (1993), and has been applied empirically to CO₂ emissions across countries in, for instance, Van Nguyen (2005), Ezcurra (2007) and Ordás Criado Grether (2011). Finally, stochastic convergence implies that shocks to per capita emissions for one country relative to another (or the average of the sample) are temporary. This is investigated seeking for stationarity using different types of unit root tests (e.g., Barassi et al., 2008; Westerlund and Basher, 2008; Nourry 2009; Yavuz and Yilanci, 2013).

The results from this research have been sensitive to the econometric approach used and the data set employed (e.g., the length of the time series, geographical coverage etc.). Overall, though, the research shows some evidence of CO₂ convergence between developed (i.e., OECD) countries but divergence at the global level. One reason for this latter result could be that countries differ significantly in terms of fossil fuel reserves, fuels which historically have been relatively costly to transport over long distances (e.g., coal, natural gas etc.). The fact that different subsets of countries yield different results (e.g., convergence among OECD countries) could be due to countries mimicking each other’s climate policies (e.g., following many countries’ ratification of the Kyoto Protocol). Another possible reason may be

differences in industrial and institutional structures, and since such structures are changing very slowly non-convergence is not unlikely, given the relative short time spans in the studies. Related to this is also the speed, or rate, of convergence; even if countries' or different economic sectors' emissions converge this may take a very long making the adjustment towards climate stabilization more difficult. For instance, the capital stock of the economy is durable and replacing industrial equipment, buildings, and infra-structure is likely to be relatively costly and a time-consuming process.

As pointed out by Pettersson et al. (2014), the CO₂ convergence research has so far devoted little attention to the underlying explanations to different emission growth paths, including the role of public policy measures (see also Never and Betz, 2014). The distribution of CO₂ emissions is strongly related to the structure of a country's economy, and this hinges on that country's natural endowments (e.g., fossil fuel reserves), development level and its comparative advantage in the production of various goods. All these conditions, in turn, are not preset requirements, but depend on the individual decisions of households, firms and governments.

In this paper we depart from these observations, and investigate the role of industry structure. Specifically, we employ the β -convergence approach and test whether different industry sectors in Sweden converge in terms of their CO₂ performance (intensity). As noted above, in contrast to previous work on CO₂ convergence our approach follows directly from an axiomatic representation of the production process taking into account that good and bad outputs are produced simultaneously. This representation can also be generalized to cases with several (good and bad) outputs, although in this paper we stick to the simple case of one bad output (CO₂ emissions) and one good output (industrial production in terms of value of sales).

This type of study can provide improved knowledge about the underlying structural determinants of convergence at the global level. For instance, if different industry structures are found to converge (conditionally) towards different steady-state levels, this would imply that countries with similar industry structures are more likely to converge while the opposite may hold for countries with different industrial composition. We also address and measure the speed of CO₂ convergence, including the role of capital intensity. As was noted in the introduction, unlike previous research on carbon dioxide convergence we focus on a unit-independent measure of carbon performance.

3. Theory and method

The theoretical approach outlined here follows primarily Färe et al. (2006) and Färe and Grosskopf (2003).² The theory is thus not novel, and the presentation in this section is motivated mainly as to make the reader aware of the basic underpinnings of the CO₂ performance index that will be used in the empirical analysis.

The environmental performance index, EP , we derive is based on neoclassical production theory. In particular this means that we will use a quantity approach based on ratios of output distance functions. It turns out, as shown below, that in the specific case of one good and one bad output this ratio of distance functions boils down to a very simple expression showing the growth path of the inverse of the emission intensity.

The distance functions are defined on the output possibility set, $P(x)$, expressed as $P(x) = \{(y, b) : x \text{ can produce } (y, b)\}$. Here y is good output, b is bad output, and x is a vector of inputs. In general, y and b are also vectors. $P(x)$ is assumed to be convex, closed, and bounded, i.e., compact, with inputs and good outputs being freely disposable. Good outputs being freely disposable is formally expressed as $(y, b) \in P(x)$ and $y' \leq y$ then $(y', b) \in P(x)$, which means that one good output can always be reduced without reducing any other output.

In addition to these technological properties, shaping the frontier of $P(x)$, additional properties must be introduced to distinguish good outputs from bad outputs. Firstly, good and bad outputs are assumed to be weakly disposable.³ This means that good and bad outputs can always be simultaneously reduced proportionally. Since bad outputs are weakly disposable, a reduction in a bad output, e.g., carbon dioxide emissions cannot be accomplished without giving up some good output, directly or indirectly. A second technological property, imposed to distinguish good outputs from bad outputs, is that (y, b) is null-joint, i.e., good output cannot be produced without producing any bad output.

² An application of this particular approach using Swedish firm level data from 1990 to 2004, in a different context, can be found in Brännlund et al. (2014) and Lundgren and Marklund (2014).

³ For good outputs, this follows from the assumption of being freely disposable, this is a sufficient condition for weak disposability.

In order to form a good output quantity index, so-called Shephard output distance functions are defined for the good output sub-vector between time periods t and $t + 1$. Specifically, we have:⁴

$$\begin{aligned} D_y^t(x^o, y^t, b^o) &= \min \left\{ \theta : \left(\frac{y^t}{\theta}, b^o \right) \in P^t(x^o) \right\} \\ D_y^t(x^o, y^{t+1}, b^o) &= \min \left\{ \theta : \left(\frac{y^{t+1}}{\theta}, b^o \right) \in P^t(x^o) \right\} \end{aligned} \quad (1)$$

The solutions, θ^* , give the maximum feasible proportional expansion of good outputs, given inputs, bad outputs and technology. As such, $D_y^t(\cdot) = \theta^*$ reflects technical efficiency in production by measuring the distance between the actual good output production level and the best-practice good output production level. By the definitions in equation (1), the good output sub-vector distance function is homogeneous of degree +1 in good output, y .

Furthermore, by letting x^o and b^o be given reference levels of inputs and bad outputs, respectively, a good output quantity index can be specified for the output vectors y^t and y^{t+1} as follows:

$$Q_y^t(x^o, b^o, y^{t+1}, y^t) = \frac{D_y^t(x^o, y^{t+1}, b^o)}{D_y^t(x^o, y^t, b^o)} \quad (2)$$

This index reflects the change in good output production from period t to period $t + 1$, holding everything else constant. Specifically, if $y^{t+1} > y^t$, then $Q_y^t > 1$, since the distance function is increasing in y . The quantity index in equation (2) satisfies some Fisher tests including homogeneity in output, being time-reversal, transitivity, and dimensionality.⁵ In the general case, including multiple good and bad outputs, all these conditions and the quantity index in equation (2) depend on the reference vector (x^o, b^o) (Färe and Grosskopf, 2003). However, in this paper we study the special case of a single good and bad output technology, which means independence from (x^o, b^o) , and as a consequence the estimation is simplified significantly.

⁴ Regarding the Shephard output distance function, Färe et al. (2006) refer to Shephard (1970).

⁵ On this account Färe and Grosskopf (2003) refer to Fisher (1922).

The quantity index being independent of (x^o, b^o) in the single good and bad output case follows from the distance function being homogenous of degree +1 in good outputs, y . From the first expression in equation (1), the homogeneity property may be stated as:

$$D_y^t(x^o, \lambda y^t, b^o) = \lambda D_y^t(x^o, y^t, b^o)$$

Setting $\lambda = 1/y^t$ gives:

$$D_y^t(x^o, 1, b^o) \cdot y^t = D_y^t(x^o, y^t, b^o)$$

Similarly, for the second expression in equation (1) we get:

$$D_y^t(x^o, 1, b^o) \cdot y^{t+1} = D_y^t(x^o, y^{t+1}, b^o)$$

Hence, the good output quantity index in equation (2) may be rewritten as:

$$Q_y^t(y^{t+1}, y^t) = \frac{D_y^t(x^o, 1, b^o) \cdot y^{t+1}}{D_y^t(x^o, 1, b^o) \cdot y^t} = \frac{y^{t+1}}{y^t} \quad (3)$$

By following the same procedure for the bad output, starting with the distance functions defined for the bad output sub-vector between time periods t and $t+1$, and contracting the bad output, we arrive at the following bad output quantity index:

$$Q_b^t(b^{t+1}, b^t) = \frac{D_b^t(x^o, y^o, 1) \cdot b^{t+1}}{D_b^t(x^o, y^o, 1) \cdot b^t} = \frac{b^{t+1}}{b^t}, \quad (4)$$

which reflects the change in bad output from period t to period $t+1$, holding inputs and the good output constant.

Finally, following the above we can specify our environmental performance index, EP , as:

$$EP^{t,t+1}(y^{t+1}, y^t, b^{t+1}, b^t) = \frac{Q_y^t(y^{t+1}, y^t)}{Q_b^t(b^{t+1}, b^t)} = \frac{y^{t+1}/y^t}{b^{t+1}/b^t} = \frac{y^{t+1}/b^{t+1}}{y^t/b^t}, \quad (5)$$

which credits good output per unit of the bad output. Then, if production of the good (bad) output increases between the time periods t and $t+1$, holding everything else constant, it will influence $EP^{t,t+1}$ positively (negatively).

From equation (5) it also clear that EP is the growth rate (plus one) of the inverse of the emission intensity index. That is, if we define the inverse to the emission intensity as $I^t = y^t/b^t$, then we have:

$$I^t = EP^{t-1,t} \cdot I^{t-1} \quad (6)$$

or

$$I^t = \prod_{i=1}^t EP^{i-1,i} \cdot I^0 \quad (7)$$

Dividing both sides of equation (7) with I^0 gives us then the accumulated environmental performance between time period 0 and t .

From equation (5) it is clear that EP can be decomposed into two components. For instance, if an industry's EP improves it can be investigated whether this is mainly due to an increase in the good output or mainly due to a reduction in the bad output, or due to a balanced combination of the two.

Finally, we can also study environmental performance at the aggregate industrial level by aggregating over the different sectors. As shown in Färe et al. (2006), environmental performance in the industry as a whole can be defined by a geometric mean of sector performances. We obtain:

$$\left(\prod_{i=1}^I \frac{y_{i,j}^{t+1}/b_{i,j}^{t+1}}{y_{i,j}^t/b_{i,j}^t} \right)^{1/I} = \frac{(\prod_{i=1}^I y_{i,j}^{t+1})^{1/I} / (\prod_{i=1}^I y_{i,j}^t)^{1/I}}{(\prod_{i=1}^I b_{i,j}^{t+1})^{1/I} / (\prod_{i=1}^I b_{i,j}^t)^{1/I}} = \frac{(\prod_{i=1}^I y_{i,j}^{t+1})^{1/I} / (\prod_{i=1}^I b_{i,j}^{t+1})^{1/I}}{(\prod_{i=1}^I y_{i,j}^t)^{1/I} / (\prod_{i=1}^I b_{i,j}^t)^{1/I}}. \quad (8)$$

The fundamentals for our empirical analysis are equations (5) and (7). Given data on good and bad outputs, we can calculate EP and I to be used in the second step, the convergence analysis.

4. Empirical approach

The empirical analysis is performed in two steps. First, we calculate the EP index at the industrial sector level based on CO₂ emissions data and the theoretical underpinnings outlined above. In the second step we specify a typical β -convergence equation with EP as the dependent variable and (lagged) I as one of the independent variables. Specifically, we focus on the so called catch-up hypothesis by analyzing cross-sector convergence of environmental

performance, or CO₂-intensity, in terms of its growth rates (i.e., β -convergence). We employ panel data for Swedish manufacturing, and regress environmental performance, EP , on initial (inverse) CO₂ emission intensity levels, I . Formally the empirical specification of our model can be written as:

$$\ln EP_i^t = \alpha_i + \beta \ln I_i^{t-1} + \boldsymbol{\gamma} \mathbf{X}_i^t + \varepsilon_i^t, \quad i = 1, \dots, N = \text{sectors}, t = 1, \dots, T = \text{time periods}, \quad (9)$$

where β , the convergence parameter, is the parameter of our central interest.⁶ A negative β indicates the existence of so-called β -convergence, suggesting that sectors with relatively low initial intensity levels catch up to the sectors with initially high levels. If this is the case it may be because the low-performing sectors can benefit from the experiences developed and used by the high-performers. These experiences can concern both technology choices as well as management strategies (e.g., the use of environmental management systems etc.).

In equation (9), \mathbf{X} is a vector of sector-specific variables with corresponding parameter vector $\boldsymbol{\gamma}$, and α_i represents sector-specific constants (i.e., unspecified fixed effects). Thus, if $\alpha_i = \alpha$ for all i , and $\boldsymbol{\gamma} = 0$, then we have absolute convergence, i.e., all sectors converge to the same steady-state emission intensity level. If the above does not hold, though, we have conditional convergence, which means that the emission growth paths differ and do not converge to the same (absolute) emission intensity level.

The specification in equation (9) can be generalized further by allowing β to vary between sectors. This would mean that we allow the speed of convergence to vary. To account for this we introduce interaction effects, and specify the following model:

$$\ln EP_i^t = \alpha_i + \beta \ln I_i^{t-1} + \boldsymbol{\mu} I_i^{t-1} \mathbf{X}_i^t + \boldsymbol{\gamma} \mathbf{X}_i^t + \varepsilon_i^t, \quad (10)$$

where $\boldsymbol{\mu}$ is the vector of interaction parameters. Without these interaction terms β represents an average over all sectors, alternatively it assumes that there is no heterogeneity over sectors. Allowing for heterogeneity, or that β depends on sector characteristics, is simply a more general model specification. For instance, a reasonable hypothesis is that capital-intensive industrial sectors will have a lower β , and thus lower speed of convergence, than the less capital-intensive sectors.

⁶ Note that this is a year-to-year, panel data specification of convergence. An alternative would be to specify a cross-sectional model that relates the mean of the environmental performance index over a time period to an initial time period intensity level. However, in our case, that reduces the data set to a point where estimation would be difficult to perform.

For our purposes the \mathbf{X} vector consists of three variables; the average (weighted) price of fossil fuels, capital intensity, and a variable addressing whether a specific share of the firms in each sector is part of the European Emission Trading Scheme (EU ETS). All of these variables may potentially have significant impacts on the growth paths of emission-intensity. The hypothesis that the sectors' EP 's have been affected by the cost of using fossil fuels, and hence the price of fossil fuels, is plausible. Although the variation over sectors of each specific fossil fuel price is fairly small, the corresponding variation for the average fossil fuel price is sometimes considerable since the mix of fuels used differs between sectors and have changed over time (see further section). We anticipate that a higher fossil fuel price will induce the industry to improve CO_2 performance.

Furthermore, we include a variable that reflects the capital intensity of each industry sector over the period. One could argue that capital-intensive sectors have more difficulties decreasing its CO_2 emissions due to the often substantial energy amounts that are needed to run a large capital stock. On the other hand, sectors with high capital-intensity may also be more motivated to save energy, and therefore invest relatively more in "green" and energy-saving technology. If so, EP would rather improve relative to less capital-intensive sectors. How capital intensity affects EP is thus ultimately an empirical question.

The EU ETS was introduced in 2005. There is a large heterogeneity both within and between industry sectors whether these are included or not in this CO_2 allowance scheme. To control for this we include a dummy variable, which takes the value of one (1) if more than 10% of the firms within a sector belongs to EU ETS at any given time period, and zero (0) otherwise.

There are of course a number of other variables that may affect the growth paths of CO_2 emission intensity, and some of these will be captured in the sector-specific fixed effects.

5. Data definitions and sources

The data used in this study have been drawn from a panel data set covering 14 Swedish manufacturing sectors over the time period 1990-2008 (SNI10-SNI37).⁷ This means that we have a total of 266 observations. In this particular application we use data on output, y (value

⁷ This data set in part emanates from Statistics Sweden industrial statistics. It has been used in other studies addressing related although different topics. For a more detailed description of the variables included, see Brännlund et.al. (2014) or Färe et al. (2014) as well as the references therein. For the CO_2 emissions we have had to exclude the emissions from coal used as input in the production process in the steel industry. The reason for this is that there have been major changes in the classification system over time, and this shows up as discrete shifts in coal use for some industries, especially the steel industry.

of sales divided by a sector-specific producer price index), CO₂ emissions, b , capital intensity (the real value of the capital stock divided by the number of employees), k , fossil fuel price (i.e., a weighted average price of all used fossil fuels), p , and the share of firms within each sector that is part of EU ETS, ETS .

The means and the standard deviations of the above variables for each sector over the entire time period are presented in Table 1, whereas the box-plots in Figures 1-2 show how the median and the variation between sectors of good and bad outputs have developed over time.

Table 1. Swedish manufacturing data: descriptive statistics, annual mean values 1990-2008 (standard deviations within parentheses. Real values, base year 1990)

Description	N	Output MSEK	CO₂ Thousand tons	Price fuel SEK/kwh	ETS share*	Capital intensity SEK
Manufacturing (total)	266	46629 (46576)	350 (457)	0.26 (0.18)	0.08 (0.12)	1206 (1361)
Mining	19	11156 (1641)	188 (39)	0.14 (0.05)	0.08 (0.00)	2676 (1670)
Food	19	89339 (4525)	636 (87)	0.26 (0.12)	0.02 (0.00)	807 (381)
Textile	19	5038 (1188)	79 (22)	0.30 (0.13)	0 (0)	451 (192)
Wood	19	36721 (11908)	73 (15)	0.36 (0.17)	0.03 (0.00)	824 (220)
Pulp/paper	19	77099 (10062)	1459 (417)	0.19 (0.09)	0.47 (0.01)	2484 (618)
Printing	19	5295 (2540)	21 (7)	0.33 (0.14)	0 (0)	373 (96)
Chemical	19	50191 (17293)	582 (302)	0.18 (0.08)	0.12 (0.01)	3649 (3101)
Rubber/plastic	19	12550 (2005)	59 (12)	0.32 (0.13)	0.01 (0.00)	515 (99)
Stone/mineral	19	15626 (2779)	419 (79)	0.13 (0.04)	0.13 (0.01)	609 (168)
Iron/steel	19	32975 (9956)	1026 (424)	0.11 (0.03)	0.22 (0.01)	1290 (225)
Fabricated metals	19	10229 (3435)	34 (20)	0.37 (0.15)	0 (0)	3491 (1625)
Machinery	19	69621 (18361)	120 (36)	0.35 (0.15)	0 (0)	890 (336)
Electro	19	101588 (64138)	44 (14)	0.33 (0.11)	0.01 (0.00)	710 (363)
Motor vehicles	19	135385 (53975)	164 (27)	0.28 (0.10)	0.03 (0.00)	1141 (287)

* the mean and standard deviations are for the years after the introduction of EU ETS.

From Table 1 it is obvious that there is a substantial variation in the data across sectors and/or over time. For instance, the CO₂ emissions range from very low in sectors such as printing, fabricated metals and rubber/plastic to considerably higher levels in pulp and paper, mining and iron and steel. The prices paid for fossil fuels also vary across the industry sectors. The main reason for this variation is that the mix of fossil fuels differs substantially across these sectors.

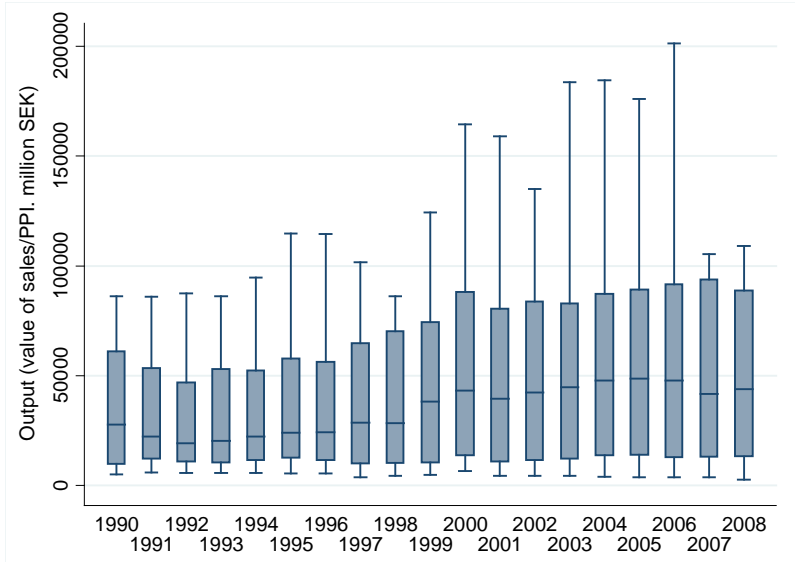


Figure 1. Industrial sales (good output) in total Swedish manufacturing, 1990-2008.

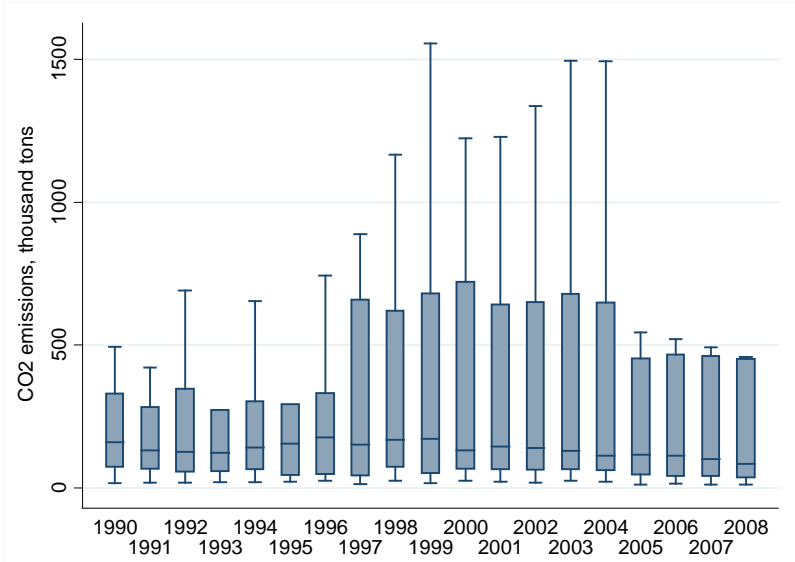


Figure 2. CO₂ emissions (bad output) in total Swedish manufacturing 1990-2008.

The box-plots in figures 1 and 2 display the median and the variation in good and bad output in each year, i.e., between sectors. The height of each box is the difference between the 75th and 25th percentiles, while the horizontal line within each box represents the median.

Concerning industrial output we see a clear upward trend, but at the same time an increase over time in the variation between sectors. This means that during the period the Swedish manufacturing industry experienced considerable structural changes. At the same time, the median CO₂ emissions display a modest negative trend, especially since the early 2000s. However, we also see that the distribution tends to become more skewed and “compact” over time. Overall Figures 1 and 2 indicate that the Swedish industry as an aggregate has improved its CO₂ performance, i.e., more is produced with fewer emissions.⁸ Another way to put it is that there appears to have been absolute decoupling in the aggregate Swedish manufacturing industry.

6. Empirical results

This section consists of two parts. In the first part we display and discuss the results from the calculations of the environmental performance index. The second part includes the empirical convergence analysis, using the results from the first part.

6.1 Environmental performance at the sector and aggregate level

The results from using equations (5) and (6) (and (8) for the aggregate manufacturing sector), i.e., the development over time of *EP* and *I*, cumulative environmental performance, for each sector is presented in the form of boxplots in Figures 3 and 4.

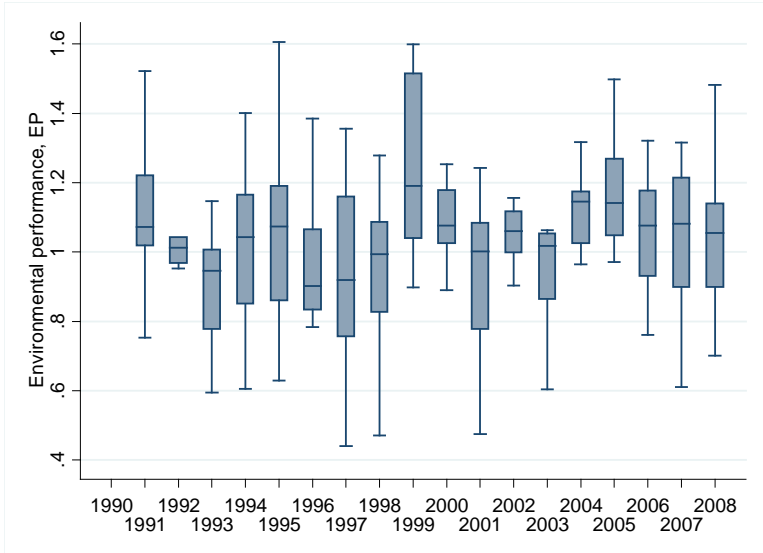


Figure 3. Environmental (CO₂) performance (*EP*) in Swedish manufacturing 1990-2008.

⁸ This corroborates the results and conclusions of Brännlund et al. (2014) using data up until the year 2004 at firm level.

Figure 3 shows that environmental performance tends to vary cyclically over time (the line within the boxes is the median over all sub-sectors). One reason for this cyclical pattern may be that good output is more sensitive to business fluctuations than the bad output, CO₂ emissions. This in turn may be because parts of the CO₂ emissions tend to be fixed in the short run, for example the emissions generated by energy for heating. It is also evident from figure 3 that the variation within years (i.e., across sectors) is fairly large, which largely is a result of the use of differing production processes

Furthermore, figure 4 reveals that the cumulative environmental performance has increased by approximately 60% over the time period under consideration. Again, on average the most significant improvements occurred after the turn of the century but also here we find significant differences across industrial sectors over the entire time period. Variation in intensity seems to have increased significantly around 1997/1998, but after that it is fairly constant.

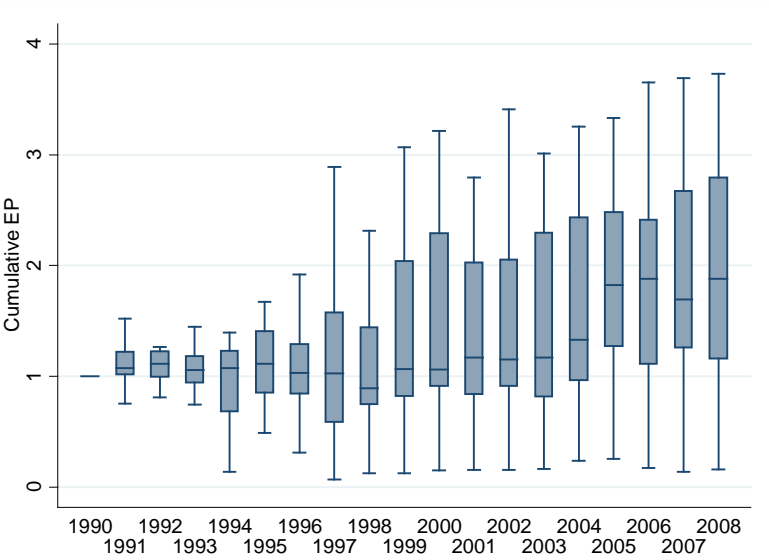


Figure 4. Cumulative environmental performance (or the inverse of emission intensity, *I*).

Finally, figure 5 displays the cumulative environmental performance for the entire manufacturing industry (geometric mean), both totally as well as decomposed into good and bad outputs. It is revealed in figure 5 that over the whole period we observe what has been called “relative decoupling” but not “absolute decoupling”.⁹ In other words, good output has grown faster than the CO₂ emissions, i.e., the emission intensity have fallen. Until

⁹ Note that if we look the medians, as in figures 1 and 2, we see absolute decoupling, but we also saw that the distribution was very skewed, which is why the geometric mean results in figure 5 show relative decoupling.

approximately the year 2000, *EP*-good changed at about the same rate as *EP*-bad, thus leaving overall *EP* fairly constant. After the year 2000, however, we see evidence of an absolute decoupling, i.e., an improvement in both of these components.¹⁰ This means, not only have emissions per unit of good output fallen; absolute CO₂ emissions have fallen. The *EP* and the cumulative *EP* index displayed above will be used in the empirical analysis below.

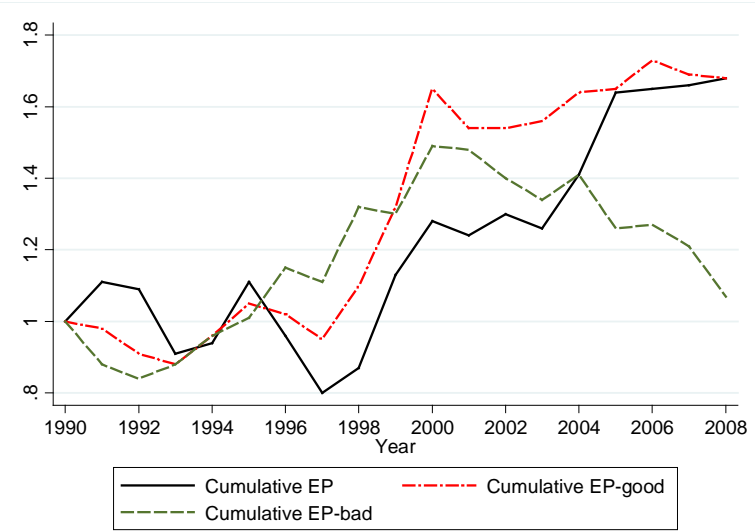


Figure 5. Aggregate cumulative environmental performance or inverse of emission intensity, decomposed into “good” and “bad”. (Index 1 = 1990)

5.2 Convergence analysis

The main objective of this paper is to analyze the development over time of CO₂ performance for the different sectors within the Swedish manufacturing industry, and investigate whether there is a convergence in emission intensity between these sectors. The basis for this analysis is equation (9). The dependent variable is thus the *EP* index for each sector, displayed in figure 3, whereas the key independent variable is the lagged cumulative *EP*, or inverse of emission intensity, presented in figure 4.

A number of different specifications of equations (9) and (10) with different types of restrictions concerning the independent variables, are estimated. Models 1-4 in table 2 include no interaction effects, but with some alterations concerning the control variables. This means that in these models β , and hence the rate of convergence, is assumed to be the same for all sectors. In Models 5-6 interaction effects are included. In all of the specifications (1-6) we include fixed effects (for each sector). The sector characteristics that we include explicitly in

¹⁰ Remember from the definition of *EP* that a decrease in *EP*-bad implies an increase in overall *EP*.

the models are the sector-specific weighted average fossil fuel prices, whether a substantial share ($> 10\%$) of the firms within a sector is part of EU-ETS, and capital intensity.

If the fixed-effects model outperforms the pooled model, while at the same time β is negative, then we cannot reject the hypothesis that there is conditional β -convergence of CO₂ performance in Swedish manufacturing. If, on the other hand, the fixed effects do not contribute to the model, we may or may not be able to reject absolute convergence. For being able to reject absolute convergence in the latter case the parameters that correspond to other sector characteristics have to be significantly different from zero.

In models 5 and 6, including the interaction effects, we can test for equality between sectors concerning the speed of convergence. A statistically significant parameter for the interaction effect implies that “ β ”, and hence the speed of convergence, depends on the particular sector characteristic, which in turn means that it in general differs between sectors.

The results from the estimations are presented in table 2. In summary, β is overall significantly negative, thus pointing at convergence in *EP* across industrial sectors. This result is robust with respect to different model specifications. The fixed effects and some of the other variables are also statistically significant, meaning that we can reject the hypothesis of absolute convergence. One important result is therefore that we cannot reject the hypothesis of conditional convergence, but reject absolute convergence. For instance, the results indicate that convergence is conditional on the average fossil fuel price. A higher fossil fuel price implies a higher *EP*, presumably since it then makes more economic sense for the industry to undertake CO₂ abatement measures.

Concerning the speed of adjustment the results indicate that there are differences between sectors, and that these at least depend on differences in capital intensity. Industry sectors with relatively high capital intensities experience a lower speed of adjustment compared to less capital-intensive sectors. Furthermore, there seems to be no effect on *EP* from participation in the EU ETS. Although this result could in part be explained by the relatively low allowance prices in the scheme during its first years, it should however be interpreted with care since there are very few observations since the introduction of EU ETS in 2005.

Table 2. Regression results, EP as the dependent variable. t -values within parenthesis.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$\ln(I^{t-1})$	-0.25 (-5.86)	-0.26 (-6.34)	-0.41 (-8.44)	-0.40 (-8.38)	-1.44 (-3.68)	-1.36 (-3.19)
$\ln(K^t)$		0.13 (3.20)	0.07 (1.78)	0.07 (1.79)	-0.50 (-2.37)	-0.55 (-2.71)
$\ln(p^t)$			0.33 (5.18)	0.34 (5.00)		0.05 (0.21)
EU-ETS				-0.02 (-0.33)		-0.01 (-0.21)
$\ln(I^{t-1})\ln(K^t)$					0.08 (3.02)	0.08 (3.12)
$\ln(I^{t-1})\ln(p^t)$						0.04 (1.23)
d2	0.32 (3.23)	0.24 (2.41)	0.29 (3.02)	0.28 (2.87)	0.27 (2.77)	0.39 (3.47)
d3	1.14 (6.00)	1.30 (6.74)	1.34 (7.31)	1.33 (7.09)	1.39 (7.24)	1.53 (7.53)
d4	0.64 (4.99)	0.82 (5.95)	0.69 (5.14)	0.68 (4.93)	0.85 (6.24)	0.82 (5.05)
d5	0.44 (4.13)	0.53 (4.91)	0.37 (3.44)	0.36 (3.32)	0.50 (4.69)	0.43 (3.24)
d6	0.83 (5.64)	0.93 (6.31)	0.93 (6.65)	0.92 (6.29)	0.93 (6.41)	1.05 (6.02)
d7	0.18 (2.00)	0.12 (1.32)	0.14 (1.62)	0.14 (1.54)	0.16 (1.78)	0.23 (2.39)
d8	0.92 (5.87)	0.99 (6.37)	1.09 (7.36)	1.09 (7.14)	0.96 (6.27)	1.20 (6.42)
d9	0.53 (4.39)	0.72 (5.43)	0.62 (4.87)	0.61 (4.72)	0.74 (5.64)	0.74 (4.78)
d10	0.16 (1.79)	0.09 (0.98)	-0.02 (-0.27)	-0.03 (-0.35)	0.15 (1.60)	0.09 (0.84)
d11	0.51 (4.38)	0.66 (5.34)	0.50 (4.14)	0.50 (4.03)	0.66 (5.39)	0.60 (4.04)
d12	0.09 (1.02)	0.19 (2.06)	0.08 (0.92)	0.08 (0.94)	0.09 (0.91)	0.00 (0.01)
d13	0.23 (2.46)	0.38 (3.70)	0.07 (0.65)	0.07 (0.57)	0.28 (2.61)	0.04 (0.31)
d14	0.77 (5.45)	0.87 (6.14)	0.76 (5.55)	0.75 (5.30)	0.88 (6.28)	0.86 (5.31)
Cons	1.37 (5.42)	-0.29 (-0.50)	3.69 (3.92)	3.68 (3.90)	8.46 (2.87)	10.73 (3.23)
Adj R2	0.15	0.13	0.22	0.22	0.16	0.25
N	252	252	252	252	252	252

Concerning the significance of the interaction effect that involves capital intensity, this implies that the speed of convergence towards the steady-state level will be lower the higher is the capital intensity of the sector. This result is consistent with the notion that capital-intensive sectors have putty-clay technologies, which provide very little short-run flexibility

in terms of factor input mixes as well as emission intensities. This in turn implies that we could expect fundamentally different convergence rates between developed countries (with overall high capital intensities), and developing countries (with low capital intensities). To some extent this may be one explanation as to why many previous studies seem to reject global CO₂ convergence, but at the same time not reject convergence among specific groups of countries (Pettersson et.al., 2014).

Figure 6 provides an illustration of how “ β ” (i.e., $\partial EP/\partial I$) develops over time for the different industry sectors as a result of changes in capital intensity (estimates based on Model 5). As can be seen there is a positive trend for all sectors, thus implying, that the rate of CO₂ performance convergence across industrial sectors is becoming lower over time. The explanation to this is that all of the sectors have become increasingly capital intensive. This type of result may also have important implications for the future dynamics of future CO₂ emissions and abatement efforts. Many scientist claims that atmospheric stabilization of the climate requires a certain amount of urgency, including relatively rapid abatement efforts in both the developed and the developing world. If the time allowed for the transition to a lower emission path is narrowed, the capital stock will need to be replaced before it wears out. As a result, overall abatement costs will increase, and in the presence of slow convergence patterns multi-lateral agreements may be more difficult to achieve. The fast growth of some Asian and African countries, considerably increasing their capital intensities may add to these difficulties.

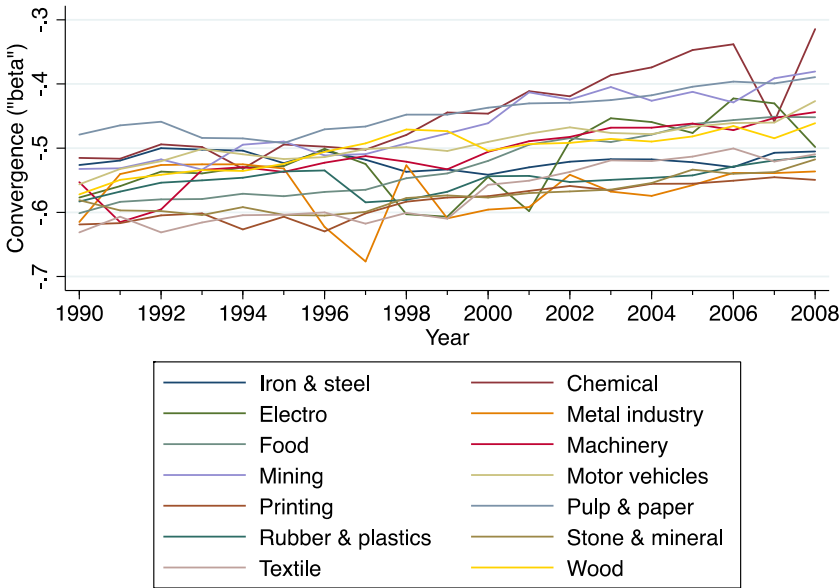


Figure 6: β -convergence of environmental performance.
 $\partial EP / \partial I = \beta + \gamma K = -1.44 + 0.08 \cdot K$

7. Concluding comments

In this paper we have provided a simple framework for the construction of an environmental performance index based on production theory. The theory provides an easy procedure in constructing an index that explicitly takes into account that firms produce good as well as bad outputs. This index is then used as the dependent variable in Solow growth type regression analysis. The main advantages with this approach is: (1) it handles goods and bads explicitly, and (2) there is no simultaneity problem between emissions and GDP, which arises in the more standard emission per-capita approach with, for instance, GDP as an explanatory variable.

The key empirical issue addressed in this study has been whether the growth rate of CO₂ emission intensity in different industries in Sweden converges to a steady state, and whether they converge to the same steady state or not. The empirical motivation is two-fold. First of all, it provides knowledge of what we can expect concerning convergence at the global level. Second, a within-country analysis may be important and interesting on its own, especially concerning the consequences for different sectors of climate and energy policies.

Our findings can be summarized as follows. First, the environmental performance index we construct is simply the rate of change in the ratio of the inverse in emission intensity. For our purposes emission intensity is defined as the ratio of CO₂ emission over production, the good output. Secondly, we show that by integrating this index we get the level of the index, or the accumulated performance. The latter is then used as the main independent variable in the regression analysis and corresponds to the (lagged) level of emissions in the more commonly used emission per-capita approach. Concerning the empirical part we tested both the unconditional and conditional β -convergence hypothesis. Here we find strong evidence in support of conditional β -convergence in CO₂ performance among the industrial sectors in Sweden.

Furthermore, by using interaction terms the results show that the rate of convergence varies significantly with capital intensity, in the sense that the higher the capital intensity is, the lower is the convergence rate to the steady state. In other words, sectors with different capital intensities will not only converge to different steady states, but also do this at different rates. The capital intensities of the Swedish industrial sectors have increased over time, thus resulting in slower speeds of convergence. This provides a micro-level illustration of the important role of capital turnover in achieving a cost-effective transition towards lower

emissions. Moreover, we also found that EU ETS participation, measured as the share of firms included in the EU ETS, did not have any significant effect on the convergence rate, or the steady state.¹¹

Most analyses, so far, concerning convergence of CO₂ emissions, have focused on per capita emissions. One reason for this is that much of the policy discussion have centered on emission obligations of an egalitarian-type of rule, such as equal emissions per capita. If emissions globally tend to converge to the same steady state, such an egalitarian rule could also be efficient. However, as pointed out in Pettersson et.al. (2014), the empirical support for such an egalitarian rule is weak. There is simply meager evidence of carbon convergence in per capita emissions at the global level, implying in turn that policies that impose equal per capita emissions are likely to generate significant re-distributional impacts and significant transfers of wealth. It is in light of this the approach taken here, looking specifically at emission intensity, may be interesting. Nevertheless, our results indicate that different industrial sectors converge to different steady states, and that capital-intensive sectors converge more slowly. In other words, similar distributional problems will appear with an allocation rule based on equal emission intensities (rather than per capita allocation).

¹¹ This corroborates to some degree Lundgren et al. (2013), who find that the EU ETS have not had a significant effect on environmentally sensitive productivity in the Swedish pulp and paper industry. Their conclusion is that the permit price has probably been too low to give incentives enough to impact environmental and/or economic performance.

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