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Endogenous Cap Reduction in Emission Trading Systems

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Abstract

Since its introduction, the European Emissions Trading Scheme (EU ETS) has been struggling with an oversupply of emission allowances and a highly volatile allowance price. One reason for the price decline is technological progress and its demand-reducing effect, which is only partially taken into account in the system. We propose a simple benchmark approach to endogenously adjust the supply of allowances to technical progress. Using a non-parametric benchmark approach, we measure the required adjustment of the allowance supply to avoid a technology-induced price decline and to maintain the incentive to invest in low-carbon technologies.

Keywords: *EU ETS, emission allowances, Data Envelopment Analysis, endogenous adjustment of supply, technological change, yardstick competition*

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1 Introduction

Prices vs. quantities? Among economists there is little doubt that a tax or a cap-and-trade market are effective tools to tackle the negative externality of GHG emissions (Gugler et al., 2021; Borenstein et al., 2019; Klenert et al., 2018; Howard and Sylvan, 2015; Aldy and Stavins, 2012; Arrow et al., 1997). Whether to regulate prices or quantities, however, is less clear. From a theoretical stance, there is no clear preference for one over the other (Weitzman, 1974). Both, price and quantity regulation, set the incentive for producers to invest in low-carbon technologies and for consumers to demand low-carbon products; consequently, both regulatory approaches should have an equivalent potential (Goulder and Schein, 2013).

Looking at existing cap-and-trade markets, doubts arise as to whether the regulation of quantities is reasonable (Aldy and Stavins, 2012). According to Weitzman (1974), price regulation via a carbon tax appears preferable as it is more efficient (Nordhaus, 2007), easier to implement, and less cumbersome to administer (Metcalf, 2019); most importantly, price regulation maintains the incentive to invest in abatement technologies as it persistently increases marginal cost. In a cap-and-trade system, the incentive declines as soon as technical progress in emission abatement is quicker than the cap adjustment (Ockenfels et al., 2020), which will finally lead to an excess supply of allowances and high price volatility (Hintermann et al., 2016).

Likewise the price of European Union allowances (EUA) in the European Emission Trading System (EU ETS) has experienced high volatility, in its young history, leading to excess supply and an allowance price often close to zero (Abrell et al., 2011). The causes to be named are manifold: excessive use of Emission Reduction Certificates (ERC), overlapping renewable support policies, or exogenous demand shocks. They all reinforce the downward pressure on the allowance price (Grosjean et al., 2016; Kollenberg and Taschini, 2019). Many policies to fight this side effect have been suggested and scrutinized in the literature: tightening the cap, allowance banking, backloading of allocated allowances, incorporating new sectors, or the Market Stability Reserve (MSR) (Fan et al., 2017; Salant, 2016). Also, it has been recognized that technical progress itself accelerates the accumulation of excess allowances in the EU ETS (Abrell et al., 2011; Aldy and Stavins, 2012; Weigt et al., 2013; Newell et al., 2014; Koch et al., 2014; Grosjean et al., 2016). But little attention has been paid to the question of how technology-induced declines in demand for allowances can be counteracted with an appropriate adjustment of the supply of allowances?

In this paper, we suggest a non-parametric benchmark approach to endogenize the supply of emission allowances that will help stabilize the allowance price thus keeping the incentive to invest in low-carbon technology up.

Using Data Envelopment Analysis (henceforth: DEA), we calculate country-specific efficiency scores as a linear combination of efficient benchmark countries, based on which we gauge the shift of their individual *technology frontier* by which the overall supply of allowances shall be reduced.

As an empirical example, we use data from the European Union Emissions Trading System (EU ETS) in order to illustrate to what extent our approach can help adjust the trading cap endogenously.[1] Our results indicate that, on average, the allowance reduction factors range between 2.13% and 2.71% in the second phase and between 2.74% and 3.59% in the third phase of EU ETS, depending on the policy associated with the respective

[1] To emphasize, we do not focus on countries' efficiency level, but on the shifts of their benchmark, i.e. their individual technology frontier.

DEA model.

In the following, we first sketch the Emission Trading System of the European Union (EU ETS) in Section (2). In Section (3), we lay out the basic concept of the endogenous adjustment model. In Section (4) we explain how to measure technical change. Section (5) contains the data description. Results are presented in Section (6), followed by a short discussion and conclusion (Section 7).

2 Managing the Allowance Surplus in the EU ETS

Every allowance trading market such as the EU ETS is based on the 'cap and trade' principle, where the cap, i.e. the total supply of allowances, determines the total of permitted emissions in the allowance market of member countries. On the installation level, each emitter have to submit the number of allowances equivalent to the emissions they produce. In the EU ETS, the owner of one European Union Allowance (EUA), has the right to emit one tonne of carbon dioxide equivalents (CO_2-eq) (Ellerman et al., 2010). The system has undergone several phases starting out with a free allocation of allowances to emitters, gradually substituting the re-partitioning of allowances by a market system.

Since its beginning, a surplus of allowance has accumulated. In 2005 (end of phase 1), the supply of allowances exceeded actual emissions by 4% – accounting for 83 million excess allowances (Ellerman et al., 2016). In the aftermath of the financial crisis in 2008/2009, overlapping national renewable support policies, an excessive use of Emission Reduction Certificates (Clean Development Mechanism, CDM), and the introduction of an EUA banking option had increased the surplus up to 1.8 billion allowances, end of phase 2 (Ellerman et al., 2016). In phase 3, the initial excess supply of 2 billion EUAs grew to 2.1 billion in 2013 (European Commission, 2015) and remained at this level during the whole period of phase 3 (Grosjean et al., 2016). Simultaneously, the allowance price had dropped significantly and so had the incentive to invest in low-carbon technology (Salant, 2016).

Ever since, the European Commission (EC) has been trying to solve the problem of excess allowances introducing a set of counteracting policies (Bocklet et al., 2019): In 2013, an EU-wide cap was set to be reduced by an annual 1.74% (= linear reduction factor, henceforth: LTF) compared to 2010 (European Commission, 2015). In 2014-2016, it was decided to backload 900 million allowances to be auctioned in Phase 3. In January 2019, the Market Stability Reserve (MSR), intended as a long-term measure, was designed to control the annual circulation of allowances and, in the event of a surplus, to transfer excess allowances to the reserve. Further reforms followed (Beck and Kruse-Andersen, 2018; Kollenberg and Taschini, 2019): The LRF was increased to 2.2% as of 2021, the MSR intake rate was doubled from 12% to 24% untill 2023 (Kollenberg and Taschini, 2019; Bocklet et al., 2019; Borenstein et al., 2019; Beck and Kruse-Andersen, 2018). All these measures were implemented to fight the excess supply of EUAs (Flachsland et al., 2020). Nonetheless, the negative pressure on the allowance price has prevailed.

The Linear Reduction Factor (LRF) is an instrument that comes closest to what we have in mind in our adjusment mechanism. This reduction factor, however, is fixed and therefore renders the system inflexible to adjust endogenously to an excess supply of allowances (Kollenberg and Taschini, 2016): any technical progress that reduces the demand for allowances more than stipulated by the LRF will lead to an excess supply of allowances which will affect the allowance price negatively.

We propose to endogenize this adjustment scheme in line with technical change. It will render the system more flexible and can easily be implemented by imposing yardstick competition on the supply of allowances.

3 Endogenous Allowance Adjustment

In this section, we first discuss the role of strategic investment behavior in low-carbon technologies of two countries. A simple duopoly model will illustrate the negative effect of technical progress in emission abatement on the incentive to invest further in such technologies. Moreover, the model shows that positive spillovers from low-carbon investment of one country to the other will steadily reduce overall efforts to invest in low-carbon technologies. In a second step, we build an allowance market, based on countries' (emission) cost function from the duopoly model.

3.1 Strategic Investment Behavior of Countries

Let us assume two countries that compete for the world demand for goods and services y.[2] For simplicity, we assume production cost per unit output to be zero so that the value of production in country i is:

$$\omega_i = (\Omega - y_i - y_j)y_i \tag{1}$$

where Ω is the price limit with y_i and y_j as production of goods and services of the respective country i and j.

Without investing in low-carbon technologies, countries have to buy one allowance per unit output for price p_0. If they invest in low-carbon technologies r, their demand for allowances shifts down. Hence, they reduce their emission cost permanently.[3] This causes spillover to other countries. A permanent reduction of a country's demand for allowances will affect price negatively, from which other countries will benefit. The spillovers affect country i's unit (emission) cost:

$$c_i(r_i, r_j) = p_0 - r_i - \beta r_j \tag{2}$$

Unit emission cost $c(r_i, r_j)$ depend on own investments r_i and country j's investment r_j, with $r_i, r_j > 0 \wedge -1 < \beta < 1$, where spillovers are conditioned by spillover parameter β. In the second stage, countries maximize the following value function:

$$\omega_i(y_i, y_j, c_i) = (\Omega - y_i - y_j - c_i)y_i - \frac{\lambda}{2}r_i^2 \tag{3}$$

incurring low-carbon investment cost $r_i^2\lambda/2$. The resulting output reaction function reads as:

$$R_i(y_j) : y_i = \frac{1}{3}\Big(\Omega - p_0 + (2-\beta)r_i + (2\beta - 1)r_j\Big) \tag{4}$$

which allows us to calculate the first-stage value function based on $\tilde{\omega}_i(r_i, r_j) = [y_i^*]^2 - r_i^2\lambda/2$ and the corresponding first-order condition $\partial\tilde{\omega}/\partial r_i$ which is:

[2] Out model builds on the model by d'Aspremont and Jacquemin (1988). It substantiates R&D investment behavior in a competitive environment. It was expanded by several authors such as Bloom et al. (2013); Lin and Saggi (2002), or Grebel and Nesta (2020) who transform the model into a n-firm oligopoly model.

[3] To keep the model simply, we do without a dynamic perspective discounting future savings in emission costs.

$$\frac{\hat{\omega}_i(r_i, r_j)}{\partial r_i} = \frac{2}{9}\Big[(\Omega - p_0) + r_i(2-\beta) - r_j(1-2\beta)\Big] - \lambda r_i = 0 \tag{5}$$

Assuming symmetric countries, equilibrium investment is:

$$r^* = \frac{2(p_0 - \Omega)(\beta - 2)}{2(\beta-1)\beta + 9\lambda - 4} \tag{6}$$

which yields optimal production value:

$$\omega^* = \frac{\gamma\left(-2(\beta-2)^2 + 9\gamma\right)(\text{p0} - \Omega)^2}{(2(\beta-1)\beta + 9\gamma - 4)^2} \tag{7}$$

It is easy to show that optimal investment r^* is monotonously decreasing in $\beta \in \langle -1, 1\rangle$:

$$\frac{\partial r^*}{\partial \beta} = \frac{2\left(2(\beta-2)^2 - 9\gamma\right)(\Omega - p_0)}{(2(\beta-1)\beta + 9\gamma - 4)^2} < 0 \tag{8}$$

Note that $2(\beta-2)^2 - 9\gamma$ reflects the second-order condition that has to be negative assuming optimal investment behavior.

Concerning the impact of low-carbon investment on production, the change of $\tilde{\omega}_i$ with respect to a change in r_i can be expressed as:

$$\underbrace{\frac{\partial \omega_i}{\partial c_i}\frac{\partial c_i}{\partial r_i}}_{\text{direct effect}} + \underbrace{\frac{\partial \omega_i}{\partial y_i}\frac{\partial y_i^*}{\partial r_i}}_{=0} + \underbrace{\frac{\partial \omega_i}{\partial y_j}\frac{\partial y_j^*}{\partial r_i}}_{\text{strategic effect}} = \gamma r_i \tag{9}$$

which states that in equilibrium, the marginal cost of investing in low-carbon technology equals its marginal returns. The first term to the left of the equality in Equation (9) denotes the direct effect of low-carbon investment r_i of country i lowering its marginal cost per unit output. This component indicates the magnitude of country i's low-carbon investment not taking spillovers into account. The second component is equal to zero because, in the first stage, the country selects its optimal level of R&D so that $\partial \omega_i / \partial y_j = 0$. The third component reflects the strategic component, which leads to the following inequality:

$$\underbrace{\frac{3\gamma(\Omega - \text{p0})}{2(\beta-1)\beta + 9\gamma - 4}}_{\text{direct effect}} + \underbrace{\frac{\gamma(1-2\beta)(\Omega - p_0)}{2(\beta-1)\beta + 9\gamma - 4}}_{\text{strategic effect}} > 0 \tag{10}$$

As the denominator of both ratios is the second-order condition, it must hold that $\gamma > \frac{2}{9}\left(2 + \beta(1-\beta)\right)$. Hence, the direct effect is always positive, whereas the indirect effect is positive for $\beta < 1/2$ and negative otherwise. Figure (1) illustrates the relationship between spillovers β, optimal low-carbon investment r^* and equilibrium output ω^*. Given the assumption that countries maximize their value function ω_i, which can also be interpreted as a country's welfare, positive spillovers will always lead to a decline in low-carbon investment r^*.

What value spillover parameter β takes, depends on the design of the allowance market as we investigate in the following.

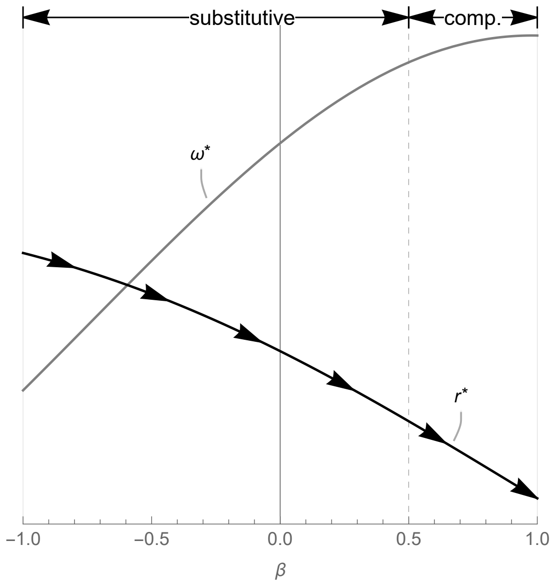

Figure 1: Equilibrium values for ω^* and r^* given β.

Nore: according to the low-carbon investment reaction functions, for $-1 < \beta < 1/2$, behavior is subsitutive, for $1/2 \leq \beta < 1$, investment behavior is complementary. Irrespective of the strategic behavior, the total production value ω^* increases, while the level of investments $r*$ will decline with increasing spillovers β.

3.2 The Market for Allowances

The demand for allowances of the two countries derives from their productive output y. Suppose one unit of output y generates one unit of emissions q, where aggregate demand for allowances Q_D depends on the price of allowances p as well as the efforts of countries i and j emission abatement efforts r_i and r_j, respectively:

$$Q_D = Q_D(p, r_i, r_j) \tag{11}$$

Since the supply of allowances is fixed, we can state that in equilibrium:

$$Q_S = S_0 \tag{12}$$

Without any investment in low-carbon technologies, the market clears with price p_0. If countries invest in low-carbon technologies, they can permanently reduce their demand for allowances per unit output, which is tantamount to saying that through low-carbon investments the demand curve shifts downward lowering the price for allowances permanently, ceteris paribus. Hence, countries benefit from positive spillovers of the other country's low-carbon investment activities.

Now, we take a closer look at countries' cost function in Equation (2). Rewriting this equation with its equilibrium values by dividing by p_0 yields:

$$\frac{c(r_i^*, r_j^*)}{p_0} = 1 - \frac{r_i^*}{p_0} - \beta\frac{r_j^*}{p_0} = 1 - \delta \tag{13}$$

where δ indicates the reduction of unit cost in percent. By construction, the reduction of unit cost is tantamount to a reduction in the demand for allowances per unit output. Consequently, the demand for allowances reduces from $q_i = y_i$ assuming no investment to $q_i = (1 - \delta)y_i$ when both countries i and j invest r^* in low-carbon technologies. In a symmetric duopoly model of the allowance market, aggregate demand thus reduces to:

$$Q_D^* = 2q^* = 2(1-\delta)y^* \tag{14}$$

This inevitably leads to a decline in the allowance price, given a constant supply of allowances. To avoid positive spillovers, the supply of allowances would need to be adjusted accordingly:

$$Q_S^* = (1-\delta)S_0 \tag{15}$$

With adjustment, the investing country would decrease its unit cost, whereas the emission cost of the not investing country would remain the same, ceteris paribus. In this case, the reduction of the allowance supply neutralizes positive spillovers, as if β in Equation (13) were set to zero. The investment of country j in low-carbon technology would not affect country i's emission cost, vice versa. Unless both countries compete on the goods market, country j's low-carbon investment would have no pecuniary effect on country i. The downside of this scenario is that it does not put any competitive pressure on country i with regard to the abatement of emissions. In order to do so, the design of the adjustment procedure must allow for negative spillovers ($\beta < 0$). This can be achieved by applying a yardstick competition approach suitable to re-partition the allowance supply of individual countries according to their relative achievements in the abatement of emissions.

The technology-induced permanent reduction in allowances δ is the sum of country-individual abatement efforts: $\delta = \sum_i \delta_i$ for $i \in \{1, 2\}$. As for stabilizing the price of allowances $\Delta Q_D = \Delta Q_S$, it must hold that

$$Q_D \sum_i \delta_i = Q_S \sum_i \alpha_i \tag{16}$$

where α_i expresses the reduction of allowances attributed to country i. Note that this requires that every country receives a certain share in total allowances. If $\alpha_i = \delta_i$, there will be no competition between countries, because then $\beta = 0$. Instead, if we set the country-specific allowance supply in the subsequent period to:

$$q_{i,t_1} = q_{i,t_0}(1 - \Delta Q_D/Q_D), \tag{17}$$

we create negative spillovers to the country with the lower efficiency gains in emission abatement. The total abatement success expressed as arithmetic mean of emission reduction is $\Delta Q_D/Q_D$. Suppose country i is the low performing country, then it holds that

$$\delta_i/q_i < \Delta Q_D/Q_D < \delta_j/q_j \tag{18}$$

In other words, reducing the allowance supply in both countries by the average technical progress (= CO_2 reduction) will generate an excess demand for allowances in country i and an excess supply of allowances in country j. Since the overall reduction of allowances is equivalent to the overall reduction in allowance demand, the allowance price will remain unchanged.

With respect to the strategic behavior of countries, this leads to the following game. Assuming a symmetric case $q_i = q_j$ with $p_0 = 1$, the corresponding pay-off matrix is reported in Table (1). The Nash equilibrium in this payoff matrix is $\delta_i = d > 0$ and $\delta_j = d > 0$. Both countries have the incentive to invest in low-carbon technology because of negative spillovers from the other country ($\beta < 0$).

		country j	
		$\delta_j = d > 0$	$\delta_j = 0$
country i	$\delta_i = d > 0$	$0\ ;\ 0$	$+\frac{1}{2}d\ ;\ -\frac{1}{2}d$
	$\delta_i = 0$	$-\frac{1}{2}d\ ;\ +\frac{1}{2}d$	$0\ ;\ 0$

Note: Parameter d represents the achieved reduction in CO_2 by the respective country. The Nash equilibrium in this payoff matrix is $\delta_i = d > 0$ and $\delta_j = d > 0$, both countries have the incentive to invest in low-carbon technology, because of negative spillovers from the other country ($\beta < 0$).

Table 1: Additional gain in allowance supply.

Our concept compares to the EU ETS in this respect that the Linear Reduction Factor (LRF) stipulates a certain reduction d, but in contrast to our model d is fixed. All member countries have to reduce their annual emissions by the LRF. If one country manages to reduce their emissions even further, the additional reduction has no negative effect on other countries. Conversely, it induces positive spillovers, since more allowances are freed causing a downward pressure on the allowance price, while leaving the allowance supply unadjusted to the extra technical progress of countries.

An endogenous adjustment of the allowance supply (i.e. and endogenous d) will stabilize the allowance price; the redistribution of extra CO_2 abatement gains, as suggested by Equation (17), creates negative spillovers ($\beta < 0$). Thus, the incentive to invest in low-carbon technologies is maintained.

It has to be stressed that the adjustment mechanism also works in the opposite direction, unless such mechanism is restricted by authority. If average emissions increased, the endogenous adjustment of allowances would lead to an increase in the allowance supply according to Equation (17), although the allowance price would remain the same, ceteris paribus.

Hence, even in times of crisis when energy supply is scarce forcing countries to switch to more carbon-intensive technologies, the proposed adjustment mechanism still works without impairing the incentive to invest in low-carbon technologies. Such investment would remain the dominant strategy. With regard to a seemingly unstoppable climate change, however, an increase in allowance supply because of an increase in demand ΔQ_D appears infeasible. In the next subsection, we show how to implement our concept.

4 Measuring Technical Change

The main requirement for the implementation of our endogenous adjustment model is the calculation of technical shifts. To do so, we proceed again in two steps. First, we explain how to measure countries' relative efficiency while taking the heterogeneity of countries' production system into account. Second, we use countries' individual benchmark efficiency, i.e. the virtual benchmark level on the technology frontier, to calculate technical shifts. To emphasize, it is not the main objective to measure the distance of inefficient countries to their reference point on the frontier. We only need to measure efficiency scores at a given time in order to compute actual shifts in the technology frontier according to which the supply of allowances has to be adjusted.

4.1 Relative Efficiency

To measure relative efficiency, we use a non-parametric approach also know as Data Envelopment Analysis (DEA) that we will explain by means of an example. For doing so, we expand the model from above beyond the duopoly case.[4] Let us assume five countries A, B, C, D, and E. All countries produce output Y using input L (=labor), while simultaneously emitting CO_2. Table (2) describes countries' production systems at time t_0. Among all five countries, country E performs best in terms of emitting the

CTRY	L	CO_2	Y	$\frac{L}{Y}$	$r_{\frac{L}{Y}}$	$\frac{CO_2}{Y}$	$r_{\frac{CO_2}{Y}}$
A	45	140	100	0.45	1	1.40	5
B	50	120	100	0.50	2	1.20	3
C	130	130	100	1.30	4	1.30	4
D	100	50	100	1.00	3	0.50	2
E	140	45	100	1.40	5	0.45	1
sum (avg)	465	485	500	(0.93)		(0.97)	

Note: initial values in period t_0; L = labor endowment; CO_2 = emissions of countries in line with the LRF; Y = output; L/Y= labor input coefficient; $r_{L/Y}$= country ranking according to labor coefficient; CO_2/Y = emissions per unit output; r_{CO_2}= country ranking according to labor input coefficient.

Table 2: Countries' production system at time t_0.

lowest amount of CO_2 per unit output Y, i.e. $CO_2/Y = 0.45$. If we assume that all remaining countries would have to meet the same environmental standards, the resulting demand for allowances whould be $\sum_i Y_i \cdot 0.45 = 225$ instead of 485[5] The corresponding δ would then be $1 - 225/485 = 54\%$ and each country would receive only 54 allowances. As a consequence, the allowance price would increase substantially. These consequence, Without delving into that discussion any further, high-income countries, such as A or B with a per capita income (Y/L) of 2.22 and 2, respectively, would probably not readily accept.

In Figure (2), we transform the figures in Table (2) into a diagram, with the coefficients CO_2/Y and L/Y depicted on the horizontal and the vertical axis, respectively. Comparing all countries, there is no country that outperforms any other country, except for country C. Country C is dominated by country B as well as country D, because it emits more CO_2 and employs more labor L per unit output than either of countries B and D. When connecting all not dominated countries by a line, as show in Figure (2), they altogether define an efficiency (or technology) frontier. All countries to the right of this frontier, i.e. country C, are inefficient according to the *Pareto-Koopmans*[6] criterion.

The degree of country C's inefficiency can be calculated as its distance to the frontier. Yet, it is unclear which of all reference points on the technology frontier is the 'right' one to use as a benchmark for country C. The calculation itself can be performed using a non-parametric approach, also known as Data Envelopment Analysis (DEA).[7] Whether a comparison of an inefficient country with a dominating one is considered legitimate, is subject of political discussion, a discussion we do not intend to lead here. Once the

[4]Grebel and Nesta (2020) show how such kind of duopoly model can be extended to the n-country case.

[5]Thereby we assuming that one unit of CO_2 equals one allowance.

[6]See Charnes et al. (1978, p.433).

[7]The underlying mathematical formulation we provide in Appendix (A).

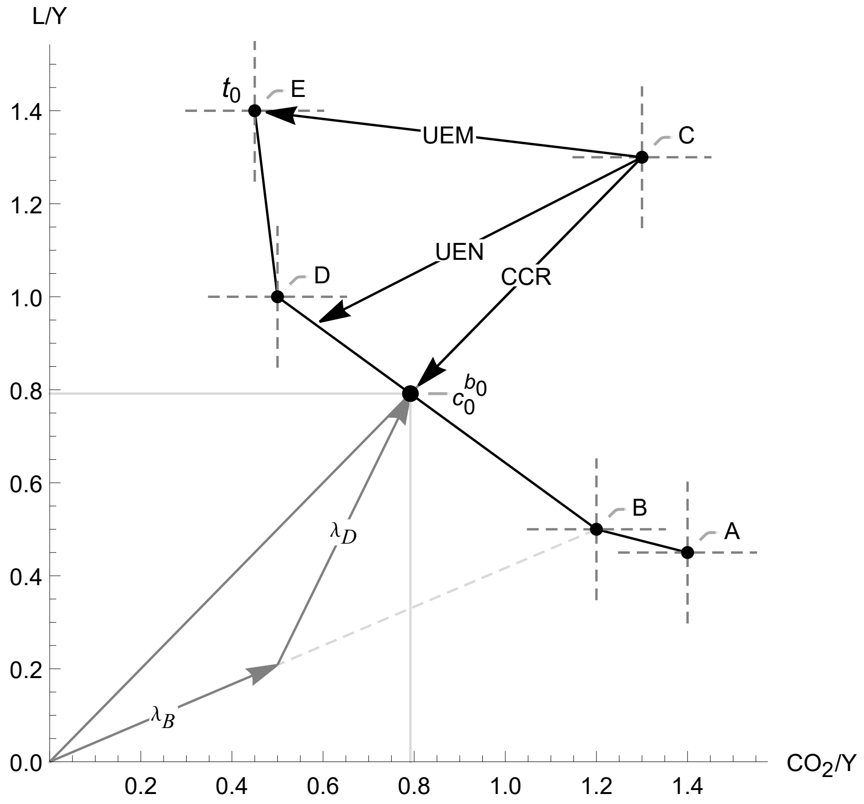

Figure 2: Non-parametric benchmark for country C.

political process has come to a consensus on the direction of economic/technical change, it can be translated into the corresponding (directional) DEA-model.

As there is no general political consensus to the best of our knowledge, we, instead consider a selection of possible policy directions by choosing various (directional) DEA models, which we label CCR, UEN, and UEM.[8] Suppose the political consensus would prescribe to achieve higher employment of input factors (L in our example) by reducing CO_2 emissions, even though it would go along with a lower labor productivity, the UEM model by Sueyoshi and Goto (2012) whould select country E as benchmark for country C (Figure 2, arrow labeled UEM).[9] Weighing the efficiency of both, input L and bad output CO_2 equally, the frontier value $c_0^{b_0}$, i.e. the linear combination of two countries (=virtual production system) B and D will be virtual benchmark as to be computed with Charnes et al. (1978)'s CCR model (Figure 2, arrow labeled CCR). If the political consensus takes a somewhat intermediate position with respect to environmental and labor efficiency, the virtual benchmark for country C would be the location on the frontier to which the arrow labeled UEN points at, in Figure (2).[10]

Before we can calculate shifts of the technology frontier t_0, required for the computation of the endogenous adjustment of bad output CO_2, we need to calculate countries' efficiency scores for each of the models we employ in our analysis. For simplicity, we start

[8]The accronyms are taken from the respective literature as specified later.

[9]The UEM model is named after the nomenclature by Sueyoshi and Goto (2012, 2013) who call it *united efficiency under managerial disposability.* For our purposes, it suffices to note that it is a directional approach favoring the abatement of bad output (i. e. emissions) as indicated by the arrow labeled UEM in Figure (2).

[10]Also, the UEN model is named accordingly as in Sueyoshi and Goto (2012, 2013), which in full is: *united efficiency under natural disposability.* Here, it suffices to note that the UEN model implies a less strict virtual benchmark than the UEM model, but a more stringent one than the CCR model.

with the traditional Charnes et al. (1978) DEA model (CCR). The underlying mathematical model is explained in Section (A).

Calculating the level of inefficiency for country C with the CCR model delivers an efficiency score $\xi_0^c = 0.61$, which denotes the ratio $\overline{Oc_0^{b_0}}/\overline{OC}$. Hence, country C would need to reduce input L and CO_2 emissions by $(1 - \xi_0^c) = 39\%$ in order to meet its benchmark level $c_0^{b_0} = (0.79, 0.79)$. The remaining DEA models are to be interpreted likewise.

4.2 Technology Shifts

Now, we turn to the measurement of technology shifts, which is required for the calculation of the endogenous parameter α. As is the case in phase III (2013-2020) of the EU ETS, where the European Commission set the minimum shift of the frontier in terms of CO_2 reduction to an annual LRF of 1.74%, measured against emissions in 2011, we start with the same idea stipulating a certain shift of the frontier. For better legibility, we multiply the LRF of the EU ETS by factor 10 assuming a LRF of 17.4%. Suppose all countries in our example manage to reduce their emissions in line with the LRF, the technology frontier in Figure (2) would shift to the left as illustrated in Figure (3). Table (3) documents the corresponding values.The frontier in t_1, as depicted in Figure (3), is

CTRY	L	$CO_{2,\mathrm{LRF}}$	Y	$\frac{L}{Y}$	$\frac{CO_2}{Y}$
A	45	115.64	100	0.45	1.16
B	50	99.12	100	0.50	0.99
C	130	107.38	100	1.30	1.07
D	100	41.30	100	1.00	0.41
E	140	37.17	100	1.40	0.37
sum (avg)	465	400.61	500	(0.93)	(0.8)

Notes: values in period t_1; L = labor endowment; $CO_{2,\mathrm{LRF}}$ = CO_2 emissions of countries in line with the LRF; Y = output; L/Y= labor input; CO_2/Y = emissions per unit output.

Table 3: Countries' production system at time t_1.

still formed by benchmark countries A_L, B_L, D_L, and E_L with subscript L indicating the shift of the frontier equivalent to a LRF of 17.4%. Remember that in this scenario it holds that $\alpha = \mathrm{LRF}$.

Suppose country B achieved a greater technology shift than stipulated by the LRF in t_1 thus reaching a higher efficiency level B_1 than in B_L, the reduction of the allowance cap would also need to go beyond the stipulated LRF reduction (i.e. $\alpha > \mathrm{LRF}$) to keep the price level unchanged. In Table 4, we document the corresponding emission levels. Column $CO_{2,\mathrm{LRF}}$, which is equivalent to the equally-labeled column in Table (3), reports the CO_2 emissions that are efficient according to the LRF, column SH indicates the corresponding country share in total CO_2 emissions. If a country manages to decrease its emissions even further, as country B in our example does, the actual emissions at the end of period t_1 will then be 373.5 units of CO_2 (column B^+), tantamount to a further reduction of -27.1 allowances. To stabilize the price of allowances, we therefore need to reduce total supply to 373.49 allowances. To impose our reduction scheme, we suggest to redistribute the additional reduction of -27.1 allowances according to the stipulated emission structure of countries as indicated by column SH. This would lead to an additional reduction of allowances as reported in column Δ, resulting in the final distribution of allowances as in column REP.

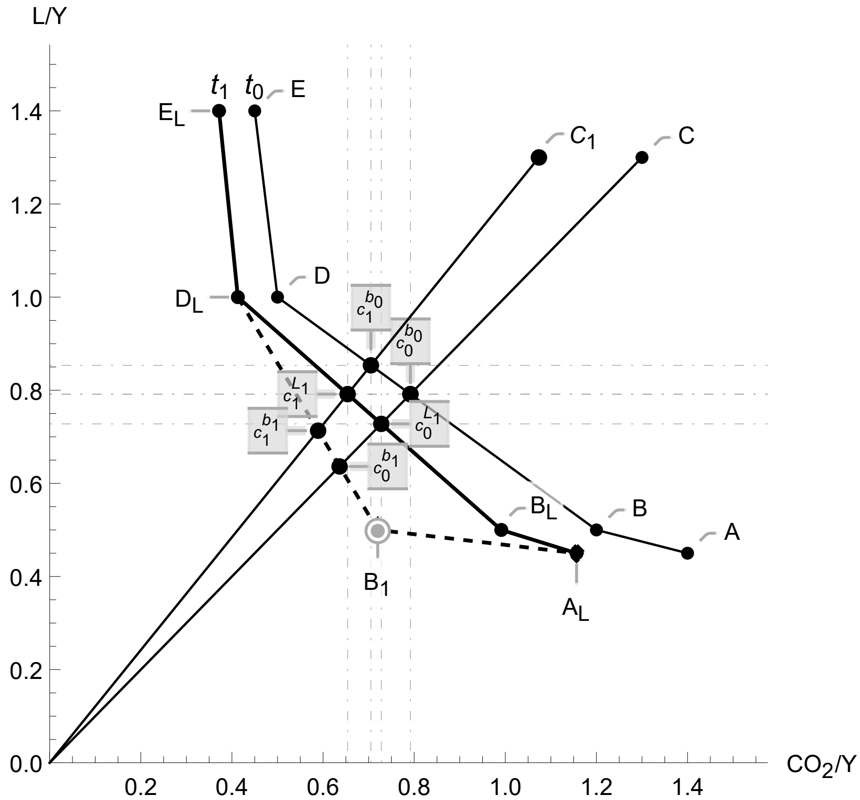

Figure 3: Technology shift and policy tools

Resuming the previous discussion, whether our adjustment mechanism imposes competition among countries: If the required reduction of allowances were only taken away from country B, i.e. the country that achieved an excess reduction, the incentive to invest in low-carbon technology would be forgone. Country B would no longer have an incentive to invest as much in low-carbon technologies. As soon as we reward country B for its additional efforts in emission abatement and simultaneously create a negative spillover to remaining countries, we generate competitive pressure between countries.

The enforced incentive structure thus imposed is revealed when subtracting column REP from column B^+. This yields column INC (=incentive) which states the negative spillovers country B imposes on remaining countries. Though country B does not earn the full amount of allowances it saved by its additional abatement efforts (i.e. 27.1), it receives a fraction of 20.4 allowances, which it can sell to remaining countries, while the latter suffer from the negative externality of country B's success in CO_2 abatement. Although they managed to comply with the LRF, they nevertheless will have to buy allowances from country B. Hence, countries not trying to excel in CO_2 abatement run the risk to be made worse off by other countries.[11]

5 Data

In this section, we apply our adjustment scheme to empirical data. To model countries' production systems, we follow the usual procedure in environmental DEA studies and use labor, capital and energy consumption as inputs, GDP as good outputs and green

[11]It must be emphasized here that a free auction system does not allow for a reallocation of allowances between countries unless it is deliberately integrated into the EU ETS. Hence, $\beta = 0$ in the case of non-integration.

CTRY	$CO_{2,\mathrm{LRF}}$	SH	B^{+}	Δ	REP	INC
A	115.6	29%	115.6	−7.8	107.8	−7.8
B	99.1	25%	72.0	−6.7	92.4	20.4
C	107.4	27%	107.4	−7.3	100.1	−7.3
D	41.3	10%	41.3	−2.8	38.5	−2.8
E	37.2	9%	37.2	−2.5	34.7	−2.5
tot(avg)	400.6	100%	373.5	−27.1	373.5	0.0

Notes: $CO_{2.\mathrm{LRF}}$ = emissions = allocated allowances in t_1 according to the LRF (compare column 'CO_2' in Table 3); SH = country shares in $CO_{2.\mathrm{LRF}}$; B^{+}= frontier shift beyond the LRF, B_L to B_1; Δ = redistribution of allowances (-27.1) according to country shares SH; REP: final amount of reallocated allowances by country; INC = incentive (i.e. negative externality) imposed by excessive progress of country B on remaining countries.

Table 4: Redistribution of allowance supply in t_1.

house gases i.e. CO_2 as bad output (Färe et al., 2004; Kumar, 2006; Zhou et al., 2010; Matsumoto et al., 2020) as well as the capacity in fossil and nuclear power production. We use non-renewable energy production capacity, instead of energy consumption, assuming that only renewable energy technology are sustainable, in the long run. In other words, increasing the use of non-renewable production capacities, be it fossil or nuclear power, will worsen countries' efficiency.[12]

The data we use are publicly available and come from three sources. Information on countries' production system such as labor, capital stock, and GDP, we retrieved from Penn World Table (PWT) for which Feenstra et al. (2015) give a detailed description. Information about countries' energy system such as CO_2 emissions, fossil and other non-renewable energy production capacity (FOSCAP) are extracted from OECD.Stat and Eurostat respectively.

We choose the variable POP (=population in mil.) from PWT as a proxy for countries' labor force (L). With regard to capital (K) and GDP (Y), we select the variable rkna (=Capital stock at constant 2017 national prices in mil. 2017 US$) and rkna (=real GDP at constant 2017 national prices in mil. 2017 US$) from PTW. We use CO_2 emissions, in thousands tonne, from the OECD as a proxy for bad output. The non-renewable energy production capacity (FOSCAP) in MW includes all energy capacities not classified as renewable. The data set ranges from the year 2003 to 2018. We take a three year moving average to smooth the data and to reduce idiosyncratic time effects.

Table 5 reports the descriptive statistics of our data that show a significant difference in countries size and their corresponding relative emissions intensity measured as the ratio of CO_2 to GDP. Moreover, the higher GDP relates to higher CO_2 emission and non-renewable energy capacity which represent the null-joint set and the disposability conditions discussed in the Appendix C.

6 Results

We first calculate countries' relative efficiency scores; as mentioned, these scores we need in order to calculate the frontier shift which we are actually interested in. We will also

[12]The production of nuclear waste also is a bad output. In account of not all countries being endowed with nuclear power, nuclear waste incurs only in countries with nuclear power. For technical reasons, as DEA requires positive vectors in inputs, good as well as in bad outputs, nuclear waste cannot enter the models as a bad output. Alternatively, we summarize all non-renewable electrical energy production capacities under the variable *FOSCAP*.

Variables	n	Mean	SD	Min	Max
K ($\times 10^9$)	322	4,751	6,098	150	20,701
L	322	20.548	24.363	0.458	83.124
Y ($\times 10^9$)	322	826	1,061	31	4,290
CO_2	322	159,351	200,233	7,183	877,997
FOSCAP	322	23018.7	28354.5	61.466	102241

Note: K: capital stock at constant 2017 national prices in bn. 2017 US$; L: population in mil.; Y: real GDP at constant 2017 national prices in bn. 2017 US$: CO_2:carbon dioxide emissions in thousands tonne; FOSCAP: non-renewable energy production capacity in MW.

Table 5: Descriptive statistics

consider country size by distinguishing between constant returns to scale (CRS) and variable returns to scale (VRS). The DEA models that we run can be consulted in Appendix (A). Aside from the traditional models, the CCR model with constant returns to scale by Charnes et al. (1978) and the BCC-model with variable returns to scale by Banker et al. (1984), we also apply the directional approaches from Sueyoshi and Goto (2012, 2013). As previously mentioned, we label their models as they do: *unified natural disposibility* (UEN) and *unified managerial disposability* (UEM), respectively. Because the first phase of the EU ETS was a pilot phase, isolated from the second and third phases in almost every dimension of the EU ETS structure (Grosjean et al., 2016), we consider only the second and the third phase until 2018.

We present the resulting efficiency scores as annual averages over the whole time span from 2008 to 2018 in Table (6). The results are multiplied by one hundred and rounded. Countries with an average efficiency score of 100 represent benchmark countries throughout the whole time span. All countries with an efficiency score of 100 are technically efficient and they form the set of countries that serve as benchmark countries for all remaining, inefficient countries. For the latter to be technically efficient, they have to reduce their CO_2 emissions, accordingly.[13] Denmark, for instance, would need to reduce its CO_2 emissions, on average, to 80% according to the CCR model. The scores show that countries significantly differ in terms of efficiency in low-carbon production. According to the CCR model (first column Table 6) countries such as Ireland, Luxembourg, Poland, and Sweden are technically efficient with an average efficiency score of 100%. On the other hand, the efficiency scores of Belgium, Czech Republic, and Slovenia range between 57% to 67% according to the CCR model. In order to be technically efficient, these countries would need to reduce their CO_2 emissions by $(1-\xi\%)$, i.e. by $(1-.57)$ to $(1-.67)$, to reach their benchmark levels. The direction itself, as pointed out in Section (3) and illustrated by Figure (2) depends on the directional distance function implicit in the respective DEA model and is subject to political discussion.

The annual virtual CO_2 benchmark is determined by multiplying actual emissions by the contemporaneous efficieny score:

$$T_{jt}^{\mathrm{DEA}} = CO2_{jt} * \xi_{jt} \tag{19}$$

which yields the virtual CO_2 benchmark $\mathrm{T_{jt}}$, calculated by the specific DEA model, for country j at time t. As final step, we now have to calculate the virtual technology shift of countries' benchmark levels for each of the six models. The shift $\delta_{jt}^{\mathrm{DEA}}$ of the virtual

[13]Note that it is the distance to the technology frontier, which decides about what variable has to be changed. To what extent CO_2 emissions and other inputs have to be reduced depends on the respective DEA model. For simplicity, we neglect remaining inputs.

CTRY	CCR	BCC	UEN_c	UEM_c	UEN_v	UEM_v
AUT	97	100	99	100	99	100
BEL	67	76	78	83	78	81
CZE	58	59	59	62	59	62
DEU	82	100	85	100	81	100
DNK	80	81	87	87	87	88
ESP	75	89	85	93	87	97
EST	69	100	59	100	45	48
FIN	81	82	79	79	70	71
FRA	86	100	92	100	94	100
GBR	81	100	87	100	88	99
GRC	54	56	67	68	70	76
HUN	75	76	77	77	81	99
IRL	100	100	100	100	98	99
ITA	79	97	88	98	92	100
LTU	89	100	90	100	89	96
LUX	100	100	100	100	100	100
LVA	86	100	92	100	100	100
NLD	83	97	86	98	84	93
POL	100	100	100	100	69	100
PRT	80	81	88	89	96	100
SVK	68	72	70	70	70	75
SVN	57	72	71	76	74	75
SWE	100	100	100	100	100	100

Note: The efficiency scores indicate annual averages over the whole time span from 2008 to 2018. For each year, the best practice frontier is constructed against which inefficient countries are compared. Each column refers to a specific DEA model. The CRS models, not taking country size into account, are CCR, UEN_c, and UEM_c, the VRS models doing so are labeled BCC, UEN_v, and UEM_v.

Table 6: Average annual efficiency score ξ in %.

technology frontier of country j simply calculates as the difference of successive annual virtual CO_2 benchmarks. Note that we decided not to use the Malmquist-index, measured as a geometric mean of piecewise shifts of the technology frontier, as it does not account for the full extent of the shift in terms of a country's virtual benchmark CO_2 levels. For $\delta_{jt}^{\text{DEA}} < 0$, the frontier shift is progressive reducing the demand for allowances by country j persistently, for $\delta_{jt}^{\text{DEA}} > 0$, it is regressive. Again, whether a regressive shift of a country's virtual benchmark should be allowed, is subject to political discussion. In times of crisis, when a supply shock impacts negatively on countries' environmental performance, it is a conceivable option; from a purely environmental viewpoint, however, only progressive shifts should be allowed for.

When allowing only progressive frontier shifts, the aggregate amount of the endogenous allowance adjustment calculates as:

$$\Delta_t^{\text{DEA}} = \sum_j^n \delta_{jt}^{\text{DEA}} \cdot I(\delta_{jt} < 0) \tag{20}$$

with I is an indicator function to capture whether $\delta_{jt}^{\text{DEA}} > 0$. In order to calculate annual allowance reduction factors, we divide Equation (20) by $\sum_{jt}^{N} CO2_{jt}$.

Table (7) reports the overall annual reduction of allowances according to our endogenous allowance adjustment scheme compared to the previous year. As we can see, the

year	CCR	BCC	$\mathrm{UEN_c}$	$\mathrm{UEM_c}$	$\mathrm{UEN_v}$	$\mathrm{UEM_v}$
2008	-1.81	-1.84	-1.86	-2.03	-1.89	-1.80
2009	-2.51	-3.50	-3.09	-2.14	-3.56	-3.35
2010	-2.09	-2.69	-2.39	-1.86	-2.78	-2.59
2011	-3.07	-3.28	-3.14	-2.61	-3.26	-2.89
2012	-2.23	-2.19	-2.11	-1.99	-2.08	-2.04
2013	-3.02	-3.21	-2.96	-2.98	-3.02	-2.89
2014	-2.74	-3.30	-2.75	-2.39	-3.11	-3.01
2015	-5.96	-3.13	-4.69	-2.38	-2.90	-2.68
2016	-4.37	-2.85	-3.84	-2.40	-2.67	-2.51
2017	-3.23	-2.30	-2.88	-2.31	-2.25	-2.18
2018	-2.22	-2.18	-2.31	-2.37	-2.10	-2.09

Note: The reduction factors are in % as compared to the previous year's emissions. Each column refers to the underlying DEA model. The column labeled CCR, for instance, indicates that, in 2008, allowances should have been reduced by 1.81% when applying the Charnes et al. (1978) model with constant returns to scale. Furthermore, we only allow for progressive shifts of the frontier in this table, i.e. $\delta_{jt}^{\mathrm{DEA}} > 0$.

Table 7: Annual allowance reduction factors in % of previous year's emissions.

endogenous allowance adjustment scheme suggests substantial allowance reduction rates throughout the study period, specially from 2013 onwards. For instance, according to the CCR model, in 2015 the emission cap should have been reduced by 5.96% compare to total emissions in 2014. In the second phase, there was no allowance reduction mechanism under EU ETS, although technical progress called for strong reductions throughout, according to Table (7). Comparing the DEA models, there is considerable variation in reduction rates. The variations are due to the different adjustment directions stipulated by the respective DEA models. Consequently, efficiency scores will differ and therewith reduction rates.

As the percentage changes refer to the previous year, it does not yet tell us whether the reductions go beyond the LRF of the EU ETS, since the LRF of 1.74 % refers to the EU aggregate emissions in 2010. To illustrate the additional reduction of allowances, we compute the difference between our endogenous reduction factor and the LRF:

$$\alpha_t^{\mathrm{DEA}} = \frac{-LRF_t + \Delta_t^{\mathrm{DEA}}}{\sum_{jt}^{N} CO_{2jt}} \tag{21}$$

where Δ_t^{DEA} denotes the amount of allowances to be reduced when applying the endogenous adjustment factor and LRF_t denotes the amount of allowances to be reduced according to the official LRF. Table (8) summarizes the additional reduction of allowances in percent of previous year's allowances according to Equation (21).

In the third phase, we find the highest additional reduction rates for the CCR model. It assumes constant returns to scale, in other words, it ignores country size when calculating efficiency scores. In general, we observe that constant-returns-to-scale models appear stricter than those with variable returns to scale. The CCR model in 2015, for instance, suggests an additional reduction of 4.09%, whereas the BCC model suggests an additional reduction of 1.26%, only.

In a more aggreated form, Table 9 compares average allowance reduction factors between the second and the third phase of the EU ETS. In 2008 to 2012, the results indicate that the emission cap could have been reduced by a further 2.13% to 2.71 % for each year compare to the previous year depending on the specific DEA models. In 2013 to 2018,

Year	CCR	BCC	UEN_c	UEM_c	UEN_v	UEM_v
2008	-0.23	-0.26	-0.28	-0.45	-0.31	-0.22
2009	-0.91	-1.90	-1.49	-0.55	-1.96	-1.75
2010	-0.43	-1.03	-0.73	-0.20	-1.12	-0.92
2011	-1.37	-1.58	-1.44	-0.90	-1.55	-1.19
2012	-0.47	-0.43	-0.36	-0.23	-0.32	-0.28
2013	-1.25	-1.44	-1.19	-1.22	-1.25	-1.12
2014	-0.92	-1.48	-0.94	-0.58	-1.30	-1.20
2015	-4.09	-1.26	-2.82	-0.51	-1.03	-0.81
2016	-2.46	-0.94	-1.93	-0.50	-0.77	-0.60
2017	-1.30	-0.37	-0.94	-0.37	-0.31	-0.25
2018	-0.29	-0.25	-0.38	-0.44	-0.16	-0.16

Note: Each column refers to a specific DEA model. The CCR column, for instance, indicates that the allowances should have been reduced by an additional 4.09% in 2015, when applying the Charnes et al. (1978) model with constant returns to scale. Only progressive shifts of the frontier where allowed so that all country-specific shifts are less or equal to zero.

Table 8: Additional reduction of allowances ($\delta_t^{\mathrm{DEA}} - \mathrm{LRF}_t$) in %.

the cap reduction factors are even stricter ranging between 2.47% and 3.59%.

The average efficiency scores from the DEA show that the EU member countries differ significantly in efficiency. The resulting allowance reduction scheme (Figure 4 and Table 7) indicate that the allowance reduction factor should have been higher than the existing LRF. Overall, the results show that due to technical change the supply of allowances should have been lower, in all years, across all policy regimes.

Model	2008-2012	2013-2018
CCRin	-2.34	-3.59
BCCin	-2.70	-2.83
UEN	-2.52	-3.24
UENvrs	-2.71	-2.68
UEM	-2.13	-2.47
UEMvrs	-2.53	-2.56

Note: The column labeled 2008-2012 indicates annual averages and, for example, suggests that the cap should have been lowered by 2.34% on average, when applying the CCR model. In 2013-2018, the supply of allowances should have been 3.59% lower under the CCR model, on average.

Table 9: Average reduction factors in % for the second and third phase.

7 Discussion/Conclusion

A cap-and-trade market will always suffer from an oversupply of allowances if allowances freed up by technical change are not taken into account by the trading system. The debate among economists and policymakers shows that continuous actions are necessary to avoid the incentive-reducing tendency of technical progress in the system. So it is not surprising that the EU ETS has experienced several amendments to tackle the issue of excess supply. Various measures were introduced such as the MSR or the LRF. All these measures help to reduce the oversupply of allowances to some extent. However, the critique we take up in this paper is that these measures do not generate any competitive pressure between countries in emission abatement.

We propose an endogenous adaptation scheme that can help overcome the challenges of a continuous, technological progress reducing the incentive for further low-carbon investments. The mechanism itself is rather simple: reduce the supply of allowances by the amount to which they are set free by countries' abatement efforts; thus we compensate for any technology-induced reduction in the demand for allowances.

To measure shifts of the best-practice frontier (i.e., the shift of countries' virtual benchmark technologies) we apply a non-parametric approach (DEA). Shifts of the frontier yield country-specific reduction schemes; they deliver the required reduction of the total allowance supply necessary to stabilize the allowance price.

With regard to the EU ETS, as it stands, it does not contain any yardstick competition on the country level. Countries operate independently from each other with respect to the reduction of emissions/allowances. Therefore, it is not enough to implement an endogenous allowance supply adjustment scheme, although this alone would help stabilize the allowance price. Without generating negative spillovers there will be no competitive pressure between countries, i.e. β in our model would remain zero despite adjusting the supply of allowances for technical progress. Some kind of award and punishment system would be required on the country level.

As for the implementation of the system, consensus on the fairness of the system among participating countries is key to successful implementation. That is why, first and foremost, the heterogeneity of countries must be reflected accordingly. Countries with a large share in high-carbon industries, for example, must not be discriminated per se against countries with a low share of such industries, vice versa. The necessary consideration of the heterogeneity of countries can be realized by a non-parametric approach. With such approach, the heterogeneity can be modeled as fine-grained as required. Arguably, the most pressing question that would need to be answered is how much heterogeneity should be allowed for? The more heterogeneity is considered, the lower the incentive to invest in low-carbon technologies. In DEA, the heterogeneity expresses in the number of inputs and outputs employed in the computation of relative performance measures (efficiency scores). The more inputs and outputs we allow, the more benchmarks will emerge. Allowing for the maximum amount of heterogeneity will make all countries efficient and thus stifle any incentive to compete.

Another point to discuss is whether, under such incentive system, countries would simply follow the benchmark country with the highest relative CO_2 emissions to avoid competition. From our point of view, it seems rather unlikely that a country transforms its industry structure solely to avoid competition for allowances. Especially since the LRF still exists to force countries into a 'clean' future. Our concept can only set an additional incentive for countries to go beyond the LRF.

Apart from all the implementation issues and additional research required for practical implementation, we believe that our endogenous adjustment system including a reward and punishment system on the country-level can help speed up the transformation toward a clean and green economy.

Appendix

A Methodology

Regarding the measurement of productivity as we use in our empirical study, various methods of parametric and non-parametric measurement methods can be found in the literature. Knittel (2002), for instance, applies a stochastic frontier analysis (parametric approach) to the coal producing industry. Fried et al. (2008) provide an in-depth overview on the details of this approach. Non-parametric approaches, i. e. data envelopment analysis (DEA) are addressed by Emrouznejad and Yang (2018). Zhou et al. (2008) collect many examples of DEA-based studies in energy and environmental economics. We choose the later approach because DEA allows an easy way to account for heterogeneity of countries and, as suggested in our endogenous cap adjustment model, facilitates the implementation of yardstick competition as motivated by Shleifer (1985) & Cantner and Kuhn (1999).

A.1 Classical DEA Models

The concept of measuring firms' productive efficiency against an efficiency frontier, as illustrated in the main text, goes back to Farrell (1957). The first using the term 'Data Envelopment Analysis' (DEA) were Charnes et al. (1978), who developed the well-known CCR[14] model to measure relative productive efficiency of decision making units (DMU), in our case, the DMUs are countries. Assuming that a DMU's size would not play a role, they constructed their model based on constant returns to scale (Førsund and Sarafoglou, 2002). In a further extension of this model, Banker et al. (1984) suggested a DEA model taking variable returns to scale (VRS) into account, a model which has become known as BCC model.

The corresponding mathematical formulation is given by Equation (23). It contains both the CCR and the BCC model. The latter just adds the inequality labeled VRS,[15] which has to be canceled to represent the CCR model. Using the same notation as Sueyoshi and Goto (2013) or Grebel (2019), we write the linear program as a system of equations with slack variables denoted d instead of inequalities, describing a set of n DMUs (j=1,$\cdots$,n) that produces a vector of s outputs ($G_j = (g_{1j}, g_{2j}, \cdots, g_{sj})^T$) while employing a vector of m inputs ($X_j = (x_{1j}, x_{2j}, \cdots, x_{mj})^T$). This is tantamount to saying that every DMU employs a technology T, expressed as a vector (x,y), apt to produce output y:

$$T = \{(x, y) : x \text{ can produce } y\} \tag{22}$$

If according to model (23) $\xi = 1$, the DMU under consideration is technically efficient, because their is no linear combination of existing technologies T that dominates the technology of the respective DMU according to the Pareto-Koopman criterion. If $\xi < 1$, the DMU is considered inefficient.

Along with the efficiency score ξ, the minimization problem in Equation (23) delivers the optimal weights ($\lambda = (\lambda_1, \lambda_2, \cdots, \lambda_n)^T$), i.e the vector of structural variables that projects inputs and output(s) of the DMU onto the best-practice frontier formed by

[14] Labels derive from the initials of the authors.

[15] Because the sum of weights $\sum_j^n \lambda_j$ must equal to 1, a small DMU, such as a small country, must not be compared to a large country.

benchmark countries.[16] For the example in Section (3), the efficiency score of country C, $\xi = 0.61$, is less than 1, it therefore is inefficient and would need to reduce its current level of inputs by 39% in order to meet its virtual benchmark level determined by the weighted linear combination of its relative benchmark country B ($\lambda_B = 0.41$) and D ($\lambda_D = 0.58$).

$$\min \xi + \epsilon \left[\sum_{i=1}^{m} R_i^x d_i^x + \sum_{r=1}^{s} R_r^g d_r^g \right] \tag{23}$$

$$\begin{array}{llllr} \text{s.t.} & \sum_{j=1}^{n} x_{ij}\lambda_j + d_i^x & = \xi x_{ik} & (i = 1, \cdots, m) & \text{(I)} \\ & \sum_{j=1}^{n} g_{rj}\lambda_j - d_r^g & = g_{rk} & (r = 1, \cdots, s) & \text{(G)} \\ & \sum_{j=1}^{n} \lambda_j & = 1 & & \text{(VRS)} \end{array}$$

$$\lambda_j \geq 0 \quad 0 \leq \theta \leq 1, \quad d_i^x \geq 0 \quad d_r^g \geq 0$$

A.2 Disposability of Bad Outputs

Both of the classical DEA models make assumptions about the underlying technology of a production system. This includes not only the assumption about returns to scale, asking to what extent size matters, the models also hypothesize about the disposability of inputs, good, and bad outputs.

Stating that a production technology $T = \{(x, g, b) : x \text{ can produce } (g, b)\}$ means that a vector b of bad outputs is defined weakly disposable, because it can only be reduced to the extent to which the vector of good outputs y is reduced. This can be expressed in line with Shephard (1970) as:

$$(x, y, b) \in T \wedge (x, \xi y, \xi b) \in T, \tag{24}$$

where parameter ξ indicates the reduction parameter for bad and good output.

In our example, when applying the CCR model, we consider bad output CO_2 as strongly disposable, because the CCR model, as well as the BCC model, assumes that bad output CO_2 can be reduced per unit of good output. In other words, bad output is strongly or freely disposable in the CCR case.[17]

This treatment, however, may be misleading (Pittman, 1983). It still is an ongoing discussion how to incorporate bad outputs into DEA. In activity analysis, to treat inputs and good outputs as strongly disposable while assuming bad outputs to be weakly disposable appears reasonable. Färe et al. (1989) point out that a substantial body of literature considers bad outputs weakly disposable (Färe et al., 1993; Ball et al., 1994; Chung et al., 1997; Tyteca, 1996, 1997). Others, such as Korhonen and Luptacik (2004), assume strong disposability of bad outputs, or propose, as Yang et al. (2007) and Jin et al. (2014) do, an individual treatment of bad outputs in accordance with bad outputs' technological specificity (Yang et al., 2007; Jin et al., 2014). A frequently cited example

[16] In all DEA models presented here, it is required that all vectors are strictly positive. As mentioned, all linear programs use a series of slack variables for inputs (d_i^x), good outputs (d_i^g) and in later models bad outputs (d_i^b). The scalar ϵ balances the impact of the inefficiency score and the amount of slacks for the degree of technical efficiency. We follow the standard procedure and set this scalar to a very small non-Archimedian number ($\epsilon = 10^{-6}$). The weights R in the objective functions above rescale slack variables d according to the range of inputs, good and bad outputs such as $R_i^x = (m+s+h)^{-1}(\max\{x_{ij}|j = 1, \cdots, n\} - \min\{x_{ij}|j = 1, \cdots, n\})^{-1}$ and $R_r^g = (m+s+h)^{-1}(\max\{g_{rj}|j = 1, \cdots, n\} - \min\{g_{rj}|j = 1, \cdots, n\})^{-1}$.

[17] Note that strong disposability is expressed by inequalities in the model.

advocating weak disposability of bad outputs is the case of coal-fired power plants that, even in the case of a technically efficient production, cannot reduce the emission of CO_2 because burning coal always emits CO_2.

Conversely, performing the analysis we have in mind on the country level, it appears plausible to assume strong disposability of bad outputs. If we are convinced that fossil fuels can be replaced by renewable energies, we implicitly assume that bad outputs must be strongly disposable in the long run. Otherwise, a zero-emission world is inconceivable. Consequently, we assume that technological change can be directed toward strong disposability of bad outputs.

Recent extensions of the disposability concept, such as proposed by Sueyoshi and Goto (2012), allows us to take an intended directional technological progress as benchmark. A DMU can either adapt to environmental policy constraints as insinuated with the arrow labeled UEN in Figure (2) by reducing bad outputs when increasing good outputs, or it could even spend additional resources, in our example labor L, to advance low-carbon technology as alluded by the arrow labeled UEM.

Sueyoshi and Goto (2012) denote their disposability concept *unified natural disposability* (UEN) and *unified managerial disposability* (UEM). Natural disposability implies that a DMU has to reduce a directional vector of bad outputs while increasing a vector of good outputs. In line with Sueyoshi and Goto (2013, 2012) or Grebel (2019), the following model measures the unified efficiency under natural disposability of DMU k:[18]

$$\mathrm{UEN}_k = 1 - \left[\xi + \epsilon\left\{\sum_{i=1}^{m} R_i^x d_i^x + \sum_{r=1}^{s} R_r^g d_r^g + \sum_{f=1}^{h} R_f^b d_f^b\right\}\right] \tag{25}$$

$$\max \xi + \epsilon\left[\sum_{i=1}^{m} R_i^x d_i^x + \sum_{r=1}^{s} R_r^g d_r^g + \sum_{f=1}^{h} R_f^b d_f^b\right]$$

$$\begin{array}{lllll}
\text{s.t.} & \sum_{j=1}^{n} x_{ij}\lambda_j + d_i^x & = x_{ik} & (i = 1, \cdots, m) & \text{(I)} \\
& \sum_{j=1}^{n} g_{rj}\lambda_j - d_r^g - \xi g_{rk} & = g_{rk} & (r = 1, \cdots, s) & \text{(G)} \\
& \sum_{j=1}^{n} b_{fj}\lambda_j + d_f^b + \xi b_{fk} & = b_{fk} & (f = 1, \cdots, h) & \text{(B)} \\
& \sum_{j=1}^{n} \lambda_j & = 1 & \text{(VRS)} & \\
& \lambda_j \geq 0, \quad \xi = URS, \quad d_i^x \geq 0, d_r^g \geq 0, d_f^b \geq 0. & & &
\end{array}$$

In analogy to Sueyoshi and Goto (2012, 2013) and Grebel (2019), DMU j out of a set of n DMUs (j=1,$\cdots$,n) produces a vector of s good outputs ($G_j = (g_{1j}, g_{2j}, \cdots, g_{sj})^T$), a vector of h bad outputs ($B_j = (b_{1j}, b_{2j}, \cdots, b_{hj})^T$) while employing a vector of m inputs ($X_j = (x_{1j}, x_{2j}, \cdots, x_{mj})^T$). The vector of unknown structural variables ($\lambda = (\lambda_1, \lambda_2, \cdots, \lambda_n)^T$) projects the inputs and the good outputs of an inefficient DMU onto the best-practice frontier formed by benchmark countries as illustrated in Figure (2).

In contrast to the CCR and the BCC model, the UEN model positions the efficiency parameter ξ into the inequalities for good (G) and bad (B) outputs, which stipulates a certain direction of technological change. With regard to disposability, inputs are assumed to be strongly disposable and bad outputs can be disposed of in the direction $\left((1-\xi)b_f^k, (1+\xi)g_r^k\right)$. Compare also Figure (2) for illustration.

The concept of managerial disposability differs only in one detail: the input inequalities (I), written in slack form, flip. This is indicated by the negative sign in front of d_i^x. The

[18] As in the CCR, slack variables, including the slacks for bad output d_f^b, are rescaled as in Sueyoshi and Goto (2013) with $R_f^b = (m+s+h)^{-1}(\max\ \{b_{fj}|j = 1, \cdots, n\} - \min\ \{b_{fi}|j = 1, \cdots, n\})^{-1}$.

reverse inequality allows for inputs such as labor and capital to be increased without loss of efficiency, as long as there is a reduction of bad output. The corresponding model (UEM) based on *managerial disposability* calculates the efficiency score ξ of DMU j as in the following:

$$\text{UEM}_k = 1 - \left[\xi + \epsilon \left\{ \sum_{i=1}^{m} R_i^x d_i^x + \sum_{r=1}^{s} R_r^g d_r^g + \sum_{f=1}^{h} R_f^b d_f^b \right\}\right] \tag{26}$$

$$\text{with:} \quad \max \xi + \epsilon \left[\sum_{i=1}^{m} R_i^x d_i^x + \sum_{r=1}^{s} R_r^g d_r^g + \sum_{f=1}^{h} R_f^b d_f^b\right]$$

$$\begin{array}{llll}
\text{s.t.} & \sum_{j=1}^{n} x_{ij}\lambda_j - d_i^x & = x_{ik} & (i = 1, \cdots, m) \text{ (I)} \\
& \sum_{j=1}^{n} g_{rj}\lambda_j - d_r^g - \xi g_{rk} & = g_{rk} & (r = 1, \cdots, s) \text{ (G)} \\
& \sum_{j=1}^{n} b_{fj}\lambda_j + d_f^b + \xi b_{fk} & = b_{fk} & (f = 1, \cdots, h) \text{ (B)} \\
& \sum_{j=1}^{n} \lambda_j & = 1 & \text{(VRS)} \\
& \lambda_j \geq 0, \quad \xi = URS, \quad d_i^x \geq 0, d_r^g \geq 0, \quad d_f^b \geq 0. & &
\end{array}$$

So far, the DEA models presented in this subsection calculate the DMU-specific virtual benchmark technology. Yet, we have not calculated the shift of the piece-wise technology frontier. As illustrated in Figure (3), to calculate shifts, we need DMU-specific benchmark values calculated on the grounds of the respective policy regime implicit to each DEA model. Overall, we have three models, each of which in two different versions when considering constant (CRS) and variable (VRS) returns to scale.

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