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19-06

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Pervasive EUAs free allocation: the case of the steel industry

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November, 2019

Abstract:

Sectors subject to international competition still benefit from free allocation of EU Allowances in Phase III of the EU ETS market. Herein we show that those free EUAs benefit the less efficient firms in terms of emissions and, by doing so, they create overallocation profits for the market leaders. This is particularly striking in the steel industry which is very concentrated with one firm producing approximately 34 per cent of the market alone. To show this, we perform a frontier analysis and show that most free permits are allocated to most polluting firms. Hence, we highlight that by protecting the EU steelmakers from international competition, free EUAs lead to a trade-off between the EU climate policy and the competition policy.

Keywords: EU ETS, steelmaking, overallocation profits, competition, CO_2 efficiency, free allocation

JEL Classification: D43, L13, Q2

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María-Eugenia Sanin acknowledges support form the Energy and Prosperity Chair.
The usual disclaimer applies.

1 Introduction

The most recent data released by the European Commission showed that the greenhouse gas emissions (GHG) regulated by the EU ETS rose for the first time in 2017. After an increasing trend from July 2017 onwards, the EUAs crossed the € 10 threshold in February 2018 reaching € 25 for the December 2018 futures. As the cornerstone of European climate mitigation policy, the EU ETS faced concerns and scepticism regarding its lack of effectiveness (Laing et al., 2013). Even though few studies showed a positive effect in terms of CO_2 reductions (Ellerman and Bunchner (2008); Ellerman et al. (2010); Egenhofer et al. (2011); Dechezlepretre et al. (2014)), especially during the first two years, others have underlined the risks of implementing such a policy and have highlighted the broader impact of the EU ETS. Additionally, since a number of countries or regional authorities have set up their own ETS, or intend to do so (*e.g.* Australia, California, China, New-Zealand, Quebec, South-Korea), an abundant litterature has emerged. The focus is not on making comparisons with other environmental public policies anymore but rather on the way to make ETS more efficient.

For instance, the question about the CO_2 price determinants raised interest among researchers especially regarding its collapse by mid-2007 and the structural changes in the scheme (Hintermann (2010); Creti et al. (2012); Aatola et al. (2013); Koch et al. (2014); Mansanet-Bataller and Sanin (2014); Ying et al. (2017)). While energy variables appear to be the most natural determinant [1], policy factors such as mechanism design can also have a strong impact on the EUAs by, for instance, being too generous with regulated firms. One of the main benefits of using cap-and-trade for emission reductions, as opposed to command-and-control methods, is that they allow for an overall reduction in emissions at minimum cost. The fact that all agents face the same price for emissions (*i.e.* the price of permits in the emissions markets), assures that, with other distortions absent, the lowest abatement cost allocation will be achieved. However, the large variety of models considered reflect difficulties in analysing such a permit market because of uncertainties of the regulatory and economic environment (*e.g.* mechanism design, national climate policies, energy prices, economic activity). In addition to price determinants studies, a large part of ETS-related literature is devoted to the effect of the EU ETS on regulated sectors' competitiveness. The extra costs induced by implementing abatement technologies or more generally by complying with climate policy requirements, are at stake in particular for firms highly exposed to international competition. Hence, the induced risk of carbon leakage is of strong interest to policy makers and attracts attention from academics.

After several years of existence and better data access, a small but growing academic literature emerged to show evidence on the effects of the EU ETS on the regulated sectors (Martin et al., 2014). These ex-post analyses confirmed ex-ante theoretical works that the effects on competitiveness are moderate as long as permit allocation is free of charge, which has been one of the responses to deal with the EU firms highly exposed to international competition. While Wagner et al. (2014) focused on French manufacturing firms and Jaraite and Di Maria (2016) on the Lithuanian industry, Petrick and Wagner (2014) used firm-level data to estimate the causal effect of the EU ETS on the regulated German manufacturing sector regarding economic criteria (employment, competitiveness) as well as CO_2 emissions. Similarly, in their ex-post econometric study Abrell et al. (2011) did not find a significant negative effect of the programme on the competitiveness of a

[1] The electricity sector is responsible for approximately 39 per cent of European CO_2 emissions.

panel of European firms, at least for Phase I and the beginning of Phase II. However, results about the effect of the EU ETS coming from this intersectoral literature might differ from one sector to another, at least in their magnitude. At the same time, a large body of the related literature aims to analyse a single sector with different methodologies, theoretically and/or empirically according to data availability. For instance, while Alexeeva-Talebl (2011) dwelt on the EU petroleum market through a cross-country analysis, Sijm et al. (2006) estimated the impact of the EU ETS on the power sector at an aggregate level by comparing a situation with and without the policy.

Here in this paper, we perform an in-depth economic analysis of the effect of the EU ETS, in particular the switch to Phase III, in terms of competition and CO_2 emission intensity. As far as we know, this intra-sectoral work is not much realised [2] because it requires data to be collected at a micro-level. Although analysis about the effect of a policy on a regulated sector gain into accuracy with firm-level data, given the existence of access restrictions to this kind of data such a task is not easy to achieve. Since it is one of the most polluting sector and it receives the most important amount of free allocation, few studies already dealt with the effect of the EU ETS on the iron and steel industry. For instance, Okereke and McDaniels (2012) conducted a qualitative assessment to show how much three steelmakers exaggerated their vulnerability to carbon pricing. Demailly and Quirion (2008) and Chan et al. (2013) found evidence that the sector was not affected by the EU ETS. According to the former, ≪ the tightening environmental stringency of the ETS in the second period should not be opposed on grounds of competitiveness losses ≫. However, they took the sector as perfectly homogeneous and used aggregated data while, according to Reinaud (2008), ≪ costs estimates for aggregate industry hide considerable intra-sector variations, and leakage rates tend to be more significant where differences are taken into account (*e.g.* differences in emission levels or in geographical location) ≫. Regarding the latter, the empirical estimation did not distinguish steel made through iron ore and recycled materials while the industrial processes differ a lot and are therefore subject to a different treatment within the EU ETS.

The article is structured as follows. Section 2 deals with the steelmaking industry and Section 3 reviews the EUAs allocation rules. Section 4 focuses on how the EU Allowances (EUAs) affect the steelmaking installations in terms of CO_2 intensity. Section 5 makes a link between competition and the EU ETS and Section 6 concludes.

2 The steelmaking industry

Globally the iron and steel industry accounts for about 7% of anthropogenic CO_2 emissions. When the mining and transportation of iron and steel are included in the calculus, the share may be as high as 10%. The sector is an essential part of the EU economy: steel is closely linked to many downstream industrial sectors such as automobile, construction, electronics, mechanical and electrical engineering. In 2009, the total sales of the steel sector amounted to 170 billions of Euros, accounting for 1.4% of the GDP of the EU's 27 Member States. The EU is the second largest producer of steel in the world, with an output of over 177 million tons of steel a year, accounting for 11% of the steel global output. In addition, the sector accounts for the highest share of CO_2 emissions from the

[2] For their empirical estimations, Fabra and Reguant (2014) used micro-level data for the Spanish electricity market and Schaefer et al. (2010) and Ye et al. (2016) for the aviation sector.

manufacturing sector, at about 27% (International Energy Agency, 2007). Most of the CO_2 in this industry results from the primary steel production based on Blast Oxygen Furnaces (henceforth the BOF process) that must be distinguished from the secondary production based on Electric Arc Furnaces (henceforth the EAF process) using ferrous scrap as main inputs instead of iron ore and coaking coke. Despite of progress in reducing CO_2 emissions between 1990 and 2010 [3], European steelmakers are subject to the EU ETS. Options for the steel industry to reduce emissions are: energy efficiency, CO_2 recovery from blast furnace gas, the use of less CO_2 intensive inputs or implementation of breakthrough technologies like the Carbon Capture and Sequestration (Gale and Freund (2001); Neuhoff and all. (2014)). Each of these options are to be considered over different timescales leading to different payback periods. For instance, investment costs in an energy efficiency improvement are covered by energy cost savings and expected to be within 2-4 years while a breakthrough technology might take a longer time to be profitable [4] (OECD, 2015).

3 EUAs allocation rules

The cap for Phase I and Phase II discriminated in terms of reduction efforts among countries in what was called the National Allocation Plans (NAPs). From Phase III there is a European-wide cap on emissions (*e.g.* in July 2010, in its Decision 2010/384/EU, the EC determined the cap from 2013 onward). Among other adjustments, a lower cap is decided. Compared to 2005, the reduction in the supply of allowances in 2020 (*i.e.* at the end of Phase III) is established to reach a reduction as compared to the 1990 levels of 21 per cent. The European Commission (EC) is currently considering tightening that target to a 25 per cent or 30 per cent reduction. Regarding the allocation rule during Phase I, about 97 per cent of EUAs were distributed for free to regulated installations and to 90 per cent for Phase II. In Phase III roughly half of the allowances are distributed through an auction while sectors considered subject to international competition, like the iron and steel sector, continue to receive EUAs for free. The way those free EUAs are allocated has interested several articles (*e.g.* Fischer (2001); Colombier and Neuhoff (2007); Sterner and Muller (2008)).

By comparing Historical-Based Allocation (HBA) and Output-Based Allocation (OBA), Quirion (2009) explained how, in HBA, a rational profit-maximising firm includes the anticipated value of emissions per unit produced in its marginal cost, that in a competitive market pushes the firm to reduce its output. The main difference between these two mechanism designs lies in the fact that with HBA, an installation received a number of allowances according to its historical emissions. Instead, in the OBA scheme, the allocation of allowances allocation is proportional to current output levels and the installation includes the value of the additional allowances received for each unit produced in their marginal revenue. In Phase I and II of the EU ETS, the HBA ruled while for Phase III, another scheme has been set up. Many studies looked at the reasons for this switch especially regarding the flaws of the initial allocation rules (*e.g.* Betz et al. (2006); Anderson and Di Maria (2011); Sartor et al. (2014)).

[3]The EU steel sector reduced its emissions of about 25%, from 298 Mt of CO_2 in 1990 to 223 Mt in 2010.

[4]The crisis of 2008/2009 weakened the financial capacities of steelmakers leading them to expect shorter payback periods.

For instance, the decentralised system led to heterogeneity of allocation mechanisms and to protect their industry, some member states tended to overallocate. The main reason is that HBA rewards the higher CO_2 intensive installation while this scheme does not take early action into account. Finally, it is now well documented that the EU ETS has been oversupplied in allowances, especially after the 2008 economic crisis. In order to address the above issues, the European Commission switched into what Meunier et al. (2014) called a capacity-based allocation, or Sartor et al. (2014) and others, a benchmark-based allocation (henceforth BBA). As explained by Branger et al. (2015), this system combines an *ex-ante* calculation of an allocation based on historical output, and an emission intensity benchmark. An adjustment can also be made according to capacity extension or reduction, plant closure and/or the arrival of new entrants.

In this case,the annual number of allowances to each installation concerned by the free allocation process (*i.e.* not auctioned), is delivered through the following formula:

$$FA_{i,p,t} = BM_p \times HAL_{i,p} \times CLEF_{p,t} \times CSCF_t$$

where $FA_{i,p,t}$ is the free allocation granted to i for its product p in time t; HAL is the historical activity level; $CLEF$ is an allocation reduction factor applied to installations considered not to be at risk of carbon leakage; $CSCF$ is a uniform cross-sectoral correction factor that can be applied to ensure that the total free allocation will not exceed the maximum annual amount of free allocation; and BM is the emissions-intensity benchmark of product p. As we can see with this formula, the BBA process in place for Phase III in the EU ETS is a combination of historical emissions (*i.e.* from HBA) and a product benchmark (*i.e.* from OBA). The level of the benchmark is of particular interest since this determines the stringency of the ETS on a determined sector, which in this case, is the iron and steel industry.

4 Heterogeneity in CO_2 and allowances among the steelmaking installations

Based on an installation-level database, we compute the CO_2 emissions intensities in the first subsection, while in the second subsection we analyse the distribution of allowances among the steelmaking installations.

4.1 Data

We use an original database with 28 steelmaking installations representing 91 per cent of EU steelmaking production (on average from 2007 to 2016) [5]. The 336 observations about crude steel production come from the annual reports of the firms and the 2016 World Steel Statistics Yearbook. Information on the features of the facilities in the EU is collected from the German Federation of steel. The CO_2 emissions, as well as the allowances allocated, are extracted from the European Union Transaction Log (EUTL) for the period 2007-2016 that we cross checked with the European Pollutant Release and Transfer Register (E-PRTR) and the database from Branger (2015).

In a nutshell, the production of crude steel in an integrated steelmaking installation requires three preceding processes namely coke making (NACE code Rev.2: 19.10), sin-

[5] We leave aside six installations because of issues with data collection.

tering (NACE code Rev.2: 07.10) and iron making (NACE code Rev.2: 24.10). The former is the conversion of metallurgic coal to coke, while the second one consists of agglomerating different grain sizes of iron ore with additives to form a material. The coke as reducing agent and the sintered ore (*i.e.* agglomerated iron ore) are then feed into a blast furnace to produce liquid iron which is called hot metal. Finally, the last step takes place in a Basic Oxygen Furnace to remove unwanted elements and as much of the residual carbon in order to convert the metal into crude steel of the required quality. Each operation holds in different units of the steelmaking installation. To assess the CO_2 emissions of our 28 installations, various system boundaries might be considered depending on the structure of flows. More precisely, installations might be connected to a power plant that recovers gases from each operation and produces electricity for steelmaking. Hence, owning such equipment is at stake for steelmakers since it represents one of the best ways of reducing emissions (Pardo and Moya, 2013). The more efficient the power generator, the cleaner the steel production will be. This plant is either owned by the furnace operator or an external electricity-producing company. However, we do not include it in the system boundaries because of issues with data access. Firstly, the share of electricity that is used for steel compared to what is injected into the local network, is unknown. Secondly, we do not know how much additional electricity might be imported since the overall electricity demand for steelmaking can be higher than what is produced in the related power plant.

Hence, in the paper, we only focus on the direct emissions which are related to the four main steps mentioned above and are needed to produce a crude steel output. On average, the share of the coking plant in total sector emissions is 9.1 per cent while for the sinter plant the share is 12.7 per cent (Ecofys, 2009). The most CO_2 intensive part of the process refers to the two other steps covering the hot metal and crude steel production with approximately 69.3 per cent [6]. The rest of the emissions are related to the downstream process (*i.e.* hot and cold rolled steel).

Using our dataset, we compute the CO_2 emission intensity for each installation i in time t, as:

$$EI_{i,t} = \frac{Emissions_{i,t}}{Crude\,steel\,output_{i,t}}$$

.

Table 1: CO_2 Emission Intensities of the EU steelmaking installations (2007-2016)

	Mean	SD over the period	SD among the installations
All installations	1.383	0.082	0.481
The 5 most efficient	0.873	0.039	0.066
The 5 less efficient	2.157	0.154	0.196

Results in Table 1 show that despite the existence of a ≪ BREF ≫ document [7] which

[6] These figures which are indications from 2005-2008, should be considered cautiously since they are ≪ extremely sensitive to small changes in the raw data and the raw data itself is prone to high uncertainties ≫.

[7] Best Available Techniques (BAT) Reference Document for Iron and Steel Production adopted within

encompasses technologies to help steelmakers to reduce their emissions, a significant gap between the less and the most efficient installations remains. The standard deviation figures over 2007-2016 show a very low variation of the CO_2 intensity of the latter. Conversely, the less efficient ones decrease (slightly) their CO_2 intensity leading to a higher standard deviation. There is also a stronger heterogeneity of CO_2 intensity among those less efficient installations, compared to the more efficient ones. Besides, we note only a few differences in the rankings of the best and least efficient installations over the period. For instance, two of the most CO_2 efficient installations in 2016 were ranked 6th and 9th in 2007, while the four less efficient installations in 2007 and 2008 are maintained as less CO_2 efficient in 2015 and 2016.

It is worth mentioning that studies on the physical drivers of CO_2 intensity highlight the role of energy efficiency determinants such as the presence of a combined heat and power solution, or various innovative technologies either used in each production step or to abate emissions. Also, the carbon content of consumed materials and the iron content of the ore, as well as the share of scrap in the steel process, can play a significant role in explaining the level of CO_2 emission intensity (Worell et al. (2001); Siitonen et al. (2010); Pardo and Moya (2013)). These factors can explain the observed heterogeneity among installations. Regarding the potential effect of the EU ETS, we do not have a structural break in the emission intensity that would be caused by the switch from Phase II to Phase III.

4.2 Distribution of allowances: BM value and Output-Based Allocation

Between 2005 and 2012, each installation was granted with free allowances regarding its past level of emissions. The switch to Phase III introduces a harmonised benchmark that is basically the average performance of the 10 per cent most efficient installations in a sector in the EU between the years 2007-2008. Installations that have an emission intensity above the BM have to buy the excess of EUAs at the market price. For the iron and steel sector, things are a little different. According to Decision 2011/278/EU (Art.11), ≪ in particular, due to a lack of data on the treatment of waste gases, heat exports and electricity production, the values for the product benchmarks for coke and hot metal have been derived from calculations of direct and indirect emissions based on relevant energy flows provided by the relevant BREF ≫. Hence, according to available data and after consultations with stakeholders, the BM for this sector has been set up as follows:

$$\begin{aligned} BM_{coke} &= 0.286\, EUA \\ BM_{sinter} &= 0.171\, EUA \\ BM_{hot\ metal} &= 1.328\, EUA \end{aligned}$$

According to the BREF document, to produce one tonne of crude steel, on average, 1.08 tonnes of iron ore and 0.359 tonnes of coke are required. These figures led us to consider that the BM for crude steel production is equal to:

$$BM_{crude\ steel} = BM_{coke} \times coke\, ratio + BM_{sinter} \times iron\, ore\, ratio + BM_{hot\ metal} \quad (1)$$

$$BM_{crude\ steel} = 0.286 \times 0.359 + 0.171 \times 1.08 + 1.328 \quad (2)$$

the IPPC Directive (2008/1/EC) and the IED Directive (2010/75/EU) for several industrial sectors.

$$BM_{crude\ steel} = 1.616 \quad (3)$$

Taking into account the four step process, the integrated steelmakers having an emission intensity equal to 1.616 t of CO_2 per tonne of crude steel, receive enough allowances to fully cover their emissions for a year. Installations that have a level below this BM will have to buy EUAs or decrease their emissions. However, if we compute a benchmark based on the common rule (*i.e.* set up for other regulated sectors) of the 10 per cent most efficient installations, we have: $\widehat{BM}_{crude\ steel} = 0.841$. Only installations emitting 0.841 tonnes of CO_2 per tonne of crude steel would fully cover their emissions with free allowances. It is less than twice the value of the BM used to deliver current allowances.

Figures 1, 2 and 3 show how much free allocations cover CO2 emissions. A rate of over 200 per cent means they have more than twice the number of allowances required to comply with the EU ETS rules. Conversely, an 80 per cent rate means that installations must buy 20 per cent of additional allowances than what they received for free. The current benchmark-based allocation is compared with alternatives namely, the estimated benchmark-based allocation and the output-based allocation.

Regarding the former, using the $\widehat{BM}_{crude\ steel}$ value, we have rebuilt the distribution of allowances in Phase III with (1). Since the iron and steel sector is considered at risk of carbon leakage we have $CLEF = 1$ for all years. The coefficient $CSCF_t$ takes the following values 0.942721, 0.926347, 0.909780 respectively for the years 2013, 2014 and 2015 (Commission Decision 2013/448/EU). The HAL value refers to the median annual production level from 2005-2008 for all installations and we have $\widehat{BM}_{crude\ steel} = 0.841$. Regarding the OBA as our second alternative allocation system, we reallocated allowances for Phase III according to the CAP of -20 per cent of the CO2 emissions from 2005 to 2020.

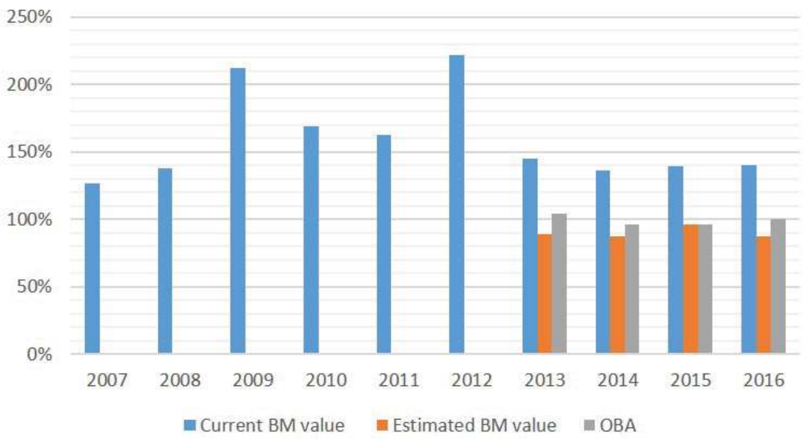

Figure 1: Average allocation for all installations

Firstly, regarding the period 2007-2012, we can clearly see the effect of the 2008 crisis, no matter what the level of CO_2 efficiency of the installations is. The collapse in steel production made CO2 emissions less intense and since allowances were delivered according to historical emissions, the oversupply was very significant. This oversupply feature is well documented in the literature and has lasted throughout Phase II.

Focusing on Phase III from 2013 to 2016, differences are significant among installa-

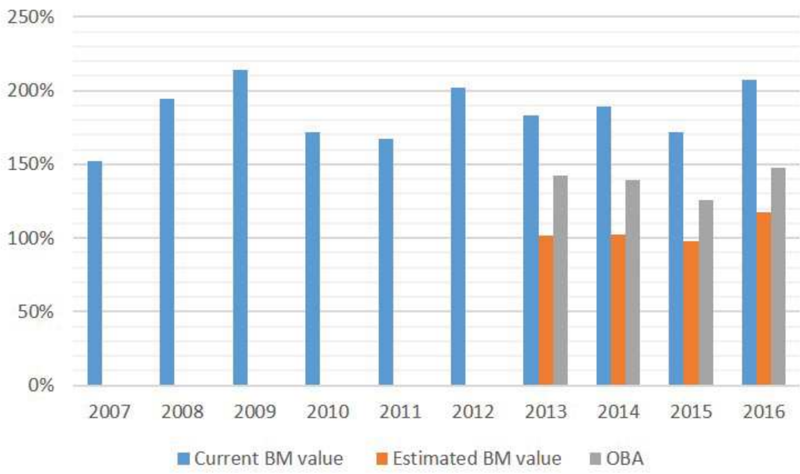

Figure 2: Average allocation for the most CO_2 efficient installations

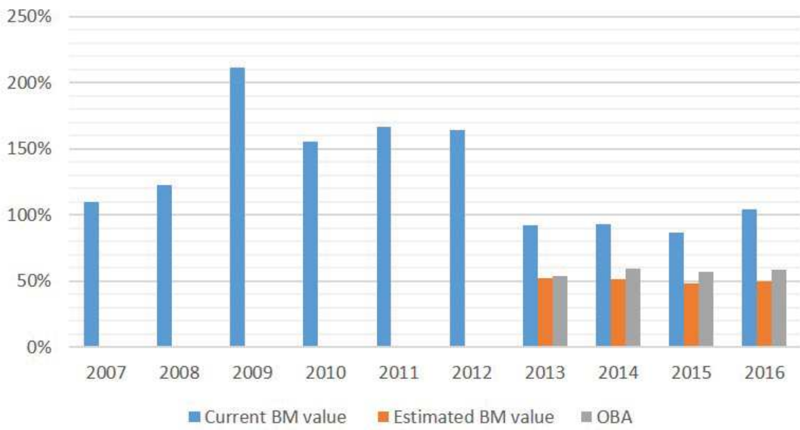

Figure 3: Average allocation for the less CO_2 efficient installations

tions. While the most efficient steelmakers still benefit from a large overallocation with the current benchmark (*i.e.* twice the level of EUAs required to fully cover their emissions), it seems that adopting new rules for Phase III made the less efficient installations, buyer of allowances for a slight proportion (assuming they choose to cover emissions through the market instead of reducing their emission intensity).

As expected, the lower estimated $\widehat{BM}_{crude\ steel}$ makes compliance with EU ETS for the less efficient installations more stringent. In addition, differences with OBA are not significant, unlike what is observed for the most CO_2 efficient installations. Indeed, such alternative allocation would allow them to still benefit from a generous overallocation.

5 EU ETS and competition

To reflect how competition can be affected by the EU ETS, in this section we shift from an installation-level to a firm-level database.

5.1 Market shares and overallocation profits

Table 2 provides a summary of our database. In addition to the absolute values of CO_2 emissions and output already used in the previous section, we have collected data on iron ore and coking coal consumption for each firm. This data comes from the 2016 Worldsteel Association Yearbook and from International Energy Agency (IEA) statistics.

Table 2: Summary statistics

	2007				2016			
	Mean	Med.	Min.	Max.	Mean	Med.	Min.	Max.
Output ('000 tons)	8 659	5 363	918	39 783	7 801	5 433	1 041	32 257
CO_2 Emissions ('000 tons)	11 885	5 593	1 156	63 966	9 733	6 491	957	42 113
CO_2 intensity	1.277	1.259	0.931	2.059	1.202	1.155	0.920	1.968
Nbr of free EUAs (thousands)	13 790	6 374	2 141	83 257	12 653	7 010	1 995	53 533
Free EUAs per ton of CO_2	1.162	1.036	0.847	1.852	1.356	1.254	0.685	2.084
Iron ore cons. ('000 tons)	12 737	8 514	2 085	55 516	11 003	7 272	1 208	44 304
Coking coal cons. ('000 tons*)	6 547	3 514	1 218	28 508	4 489	2 643	1 063	19 409
Number of firms (installations)	13(28)				12(25)			
Average price of EUAs (Euros)	24.2				5.3			

**Note: Data for coking coal consumption in 2016 being not available, we use data from 2015.*

Like we can see on Table 3, the production of crude steel is dominated by a leader representing more than 33% of the market. Three other firms follow with on average more than 10% of market shares throughout the sample period. The rest of the supply is provided by steelmakers who own on average between 1% and 7%. Besides, the standard deviation results do not show significant variations in the market sharing from 2007 to 2016.

Table 3: Market shares and Standard Deviations over the period 2007-2016

	Mean	SD
Arcelor Mittal	0.338	0.0092
ThyssenKrupp	0.142	0.0088
Tata Steel	0.140	0.0086
Riva Group	0.067	0.0104
Voestalpine	0.056	0.0032
SSAB	0.057	0.0032
Salzgitter AG	0.062	0.0045
US Steel	0.045	0.0032
Dillinger Hütte	0.025	0.0016
Moravia Steel	0.027	0.0024
Saarstahl	0.025	0.0033
ISD Dunafer	0.014	0.0033

Since the firms are granted with more free allocations than what they need to fully cover their emissions and based on the overallocation shown in the previous section, the iron and steel industry might benefit from important overallocation profits [8]. They are computed for each firm with the excess of allowances and the yearly average price of the EUA. Figure 4 highlights the tremendous gap between firms, in absolute terms. With € 4,295 billion, the leader has even more than twice the overallocation profits of the second steelmaker (€ 1,987 billion), and it represents three times more than the third one (€ 1,153 billion). Regarding the top five steelmakers benefiting from the EU ETS, our results are in line with what Sandbag (2011) observed before 2011 and called the ≪ Fat Cats ≫. However, our estimations slightly differ in two points. Firstly, we have left aside a few installations from our database because of data issues regarding their level of output. Secondly, cumulated overallocation profits are computed with a yearly average price, which means that steelmakers are assumed to sell their surplus of EUAs each year. Instead, Sandbag (2011) used a constant value of € 17 (06/05/2011) which means that they assume that steelmakers sell their surplus at the end of the sample period 2008-2010.

Relative to what the firm produced, this overallocation profit is rebalanced between the leader and the main steelmakers, but a gap remains with the five smaller producers (Figure 5).

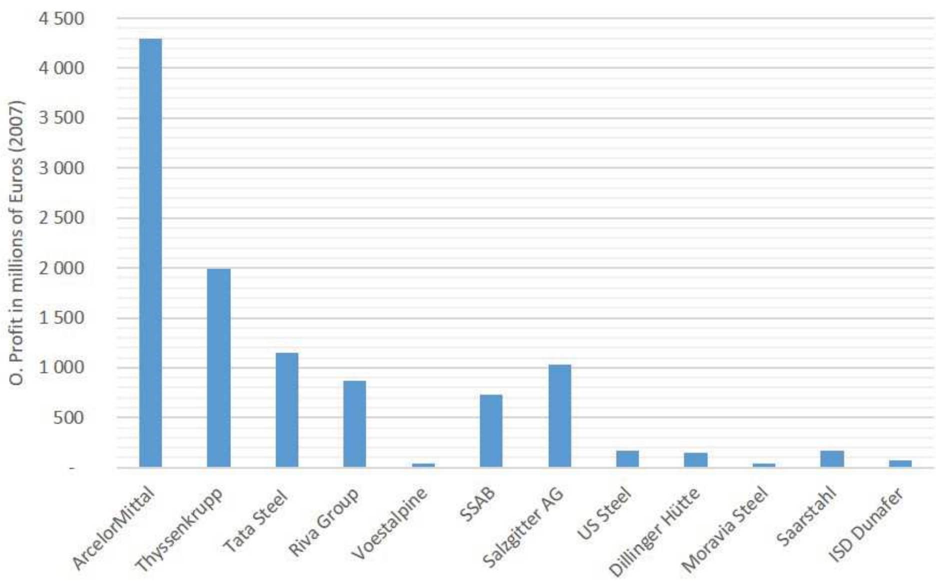

Figure 4: Cumulated overallocation profit from 2007 to 2016 (in absolute terms)

[8]According to Branger (2015), ≪ overallocation profits can be distinguished from windfall profits, which refer to the profits from free allocation where emitters additionally profit from passing on the marginal CO_2 opportunity cost to product prices, despite receiving the allowances for free. Overallocation profits can occur even in the absence of cost pass through, if output falls short of historical levels ≫.

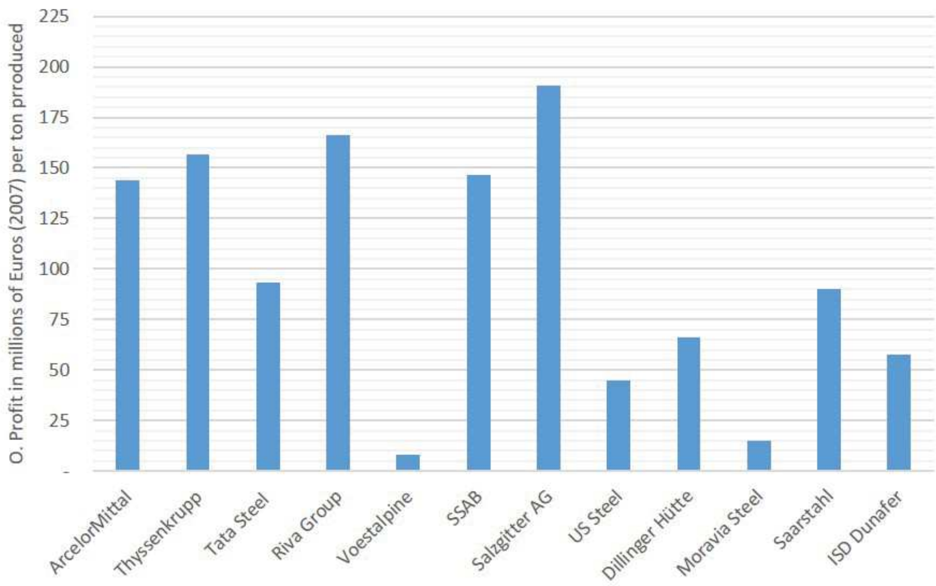

Figure 5: Cumulated overallocation profit from 2007 to 2016 (per ton produced)

To reflect this heterogeneity better, Table 4 presents the share of the individual overallocation profit compared to the overall one granted to the iron and steel sector according to the EU ETS Phases. In 2007 (*i.e.* the last year of Phase I), results show that the leader captured slightly less than 80 per cent of the total overallocation profit while the negative values show that the EU ETS was costly for a few firms. A readjustment of the overallocation profit sharing occured in Phase II, to the detriment of the leader and in favour of the three other main steelmakers. This trend is also observed in Phase III where the main producers have an equivalent share of the overall overallocation profit (except Tata Steel).

Table 4: Share of the firm's overallocation profit with respect to the overall granted to the sector

	Phase 1 (2007)	Phase 2 (2008-2012)	Phase 3 (2013-2016)
Arcelor Mittal	0.777	0.397	0.244
ThyssenKrupp	-0.049	0.198	0.244
Tata Steel	0.102	0.115	0.100
Riva Group	-0.042	0.055	0.257
Voestalpine	0.028	-0.003	0.034
SSAB	0.144	0.065	0.042
Salzgitter AG	-0.001	0.114	0.042
US Steel	-0.003	0.025	-0.031
Dillinger Hütte	0.004	0.015	0.005
Moravia Steel	-0.002	0	0.029
Saarstahl	0.004	0.018	0.006
ISD Dunafer	0.039	0	0.028

Finally, by computing the average overallocation profits of Phase III with our alternative allocation using the $\widehat{BM}$ value, we illustrate in Figure 6 the firms that benefit the most from undervaluation of the benchmark and still make important overallocation profits, which they should not do. The wider the gap between orange and blue bars, the more ≪ unfair ≫ the distribution of overallocation profits appears to be.

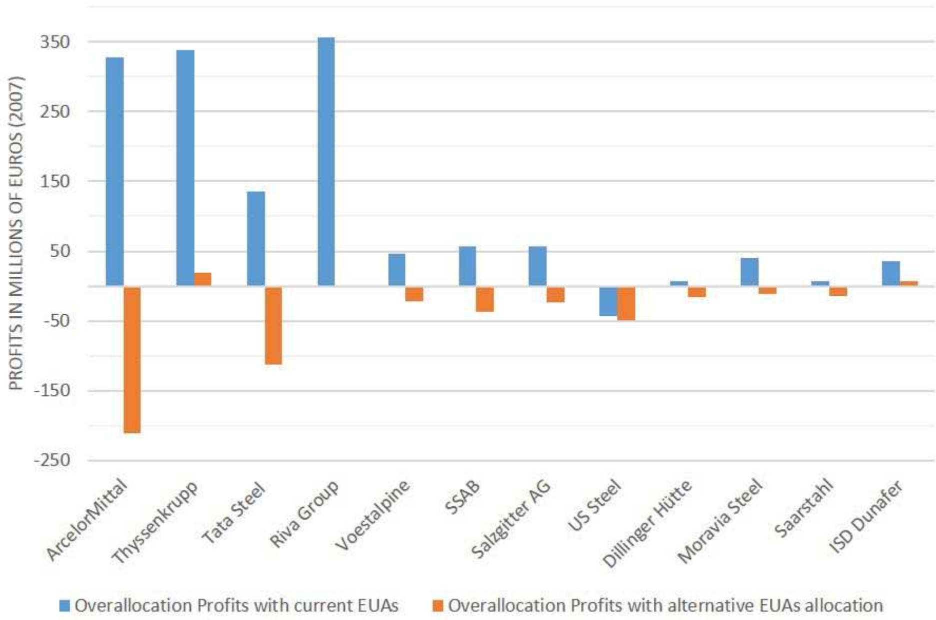

Figure 6: Overallocation profits of 2013-2016 with the current BM compared to our estimated BM

With the current allocation method, the free allowances are considered subsidies and seem to benefit the most dominant firms, even when overallocation per ton of output is considered. This does not help the market to be more competitive, although we observe that the market shares remained constant over the period 2007-2016. While EUAs are provided for free in order to protect from international competition, such a measure seems to have a negative effect on EU competition and does not help the efficiency of the EU climate policy. Hence, a trade-off between EU competition law and EU climate policy arises.

In addition, we might wonder whether at least the apparent unfair sharing of overallocation profits corresponds to the CO_2 emissions performance of the firms.

5.2 Measuring efficiency with a DEA-based environmental performance evaluation

To assess the efficiency and provide information on the rankings of the firms in terms of their relative CO_2 emission performance, we use a Data Envelopment Analysis model (DEA) [9]. Unlike the standard DEA models, we integrate environmental externalities as an undesirable output. A Directional Distance Function technique representing the distance between observed and efficient fictive values, is used. Basically, it allows us to estimate

[9]For methodological details, see Appendix A

how much the installation's efficiency can be improved relative to the level reached by the most efficient installations.

The twelve firms in our database produce a crude steel output with the following two main materials: coking coal and iron ore. The firms also produce an undesirable output which is the volume of CO_2 emissions. From this data, we can compute the material consumption intensity for each firm and the efficient frontier regarding the two periods before and after the switch of the EU ETS allocation methods (Figure 7). We first observe that ISD Dunafer and Voestalpine remain the most efficient firms between the two periods, compared to the others. The latter even decreased its intensity in both inputs. These two firms established on the best-performing practice frontier, are used as a reference of comparison for the inefficiently performing firms.

We also point out the relative distance to the efficient frontiers of the two main steelmakers: ArcelorMittal and ThyssenKrupp. While the latter seems to have decreased its relative input intensity between Phase II and III (*i.e.* the length of the orange solid arrow is shorter than the length of the orange dashed arrow), it seems that ArcelorMittal has improved its relative consumption of input per output, compared to the most efficient firms.

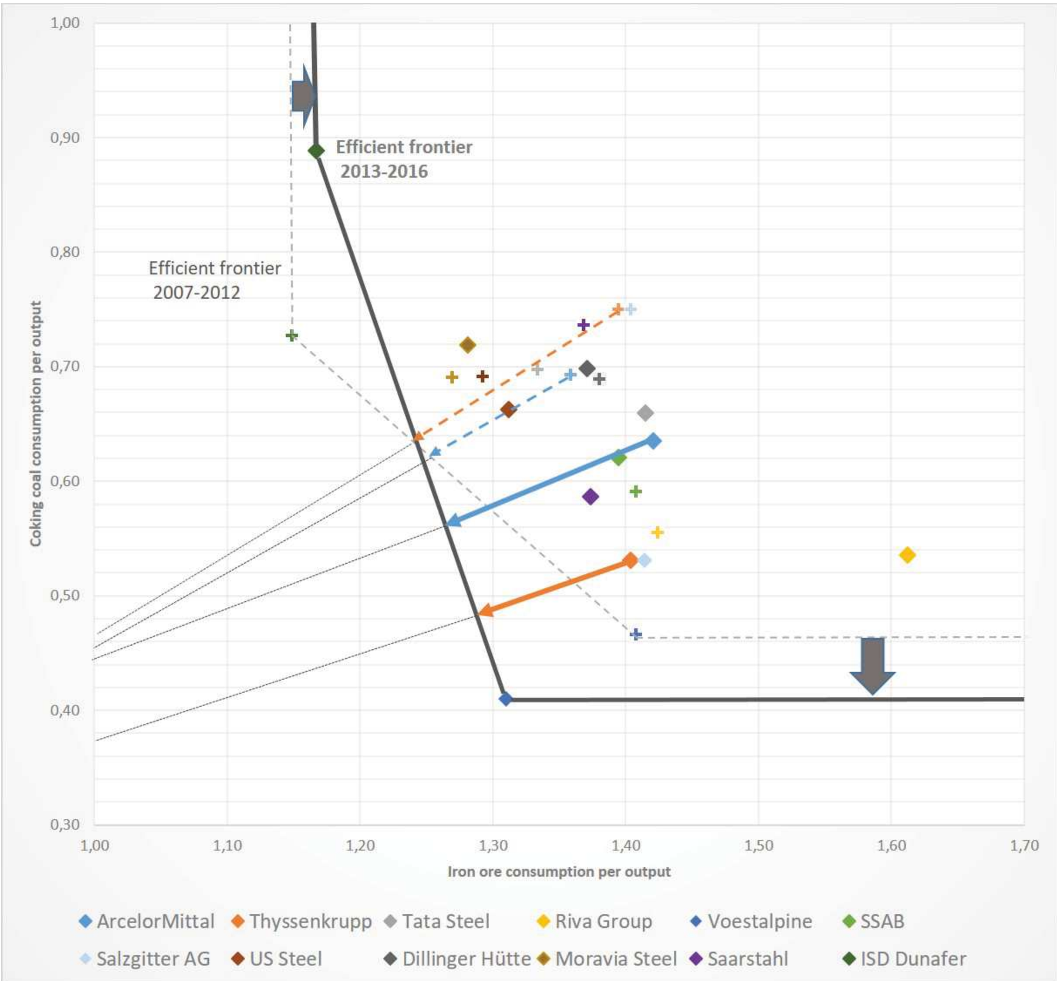

Figure 7: Input intensities and efficient fontiers for the periods 2007-2012 and 2013-2016

Unlike what is expected in theory, here the leader is not the most efficient firm in consumption of inputs. Among other reasons, this can be explained by a vertical integration strategy set up by ArcelorMittal and Tata Steel. By buying mining assets it allowed them to rely less on the soaring prices that occurred throughout 2000s [10]. For instance, regarding the iron ore which, in 2011, represented approximately 40 per cent of the total cost in steelmaking (Faure, 2012), the price rose from US$ 12 per tonne in 2002 [11] to more than US$ 150 per tonne, ten years later. In addition, ArcelorMittal entered into the European market through an external growth strategy. Their choice in buying installations might have been made according to other input costs such as labour and energy, which represented respectively 10 per cent and 12 per cent of the total cost in 2011. The former appears to be lower in the Central and Eastern European countries like Romania and Poland where ArcelorMittal invested, while the latter appears to be very low in France, where the firm also bought big integrated steel plants in 2006. However, gains from lower costs of input per output might be counterbalanced by the level of technology in each installation.

Given this distribution of material intensities and the level of CO_2 emissions for each firm we can compute the relative CO_2 emission efficiency score, thanks to the linear model defined in Appendix A (7) and based on our cross-sectional data. Results shown in Appendix B allow us to rank firms yearly between 2007 and 2015, as presented in Table 5.

Table 5: Rankings from the CO_2 emission performance scores of the steelmaking firms (2007-2015)

Firm	Average	2007	2008	2009	2010	2011	2012	2013	2014	2015
Voestalpine	1	1	1	1	1	1	1	1	1	1
ISD Dunafer	2	1	1	1	1	1	1	1	4	1
Salzgitter AG	3	1	2	5	4	2	3	2	2	2
Moravia Steel	4	1	1	1	5	5	4	3	1	5
SSAB	5	3	4	1	1	6	6	6	5	11
US Steel	6	5	9	4	3	9	7	1	6	7
Tata Steel	7	1	5	1	10	11	2	9	3	3
ThyssenKrupp	8	4	3	7	7	7	9	5	9	4
Riva	9	2	6	3	2	10	5	10	10	9
Dillinger Hütte	10	8	8	6	6	3	10	7	8	8
Saarstahl	11	6	7	8	9	8	11	4	7	6
ArcelorMittal	12	7	10	2	8	4	8	8	11	10

We observe that including CO_2 emission intensity in the analysis does not prevent the two firms on the efficient frontier (Figure 7), namely Voestalpine and ISD Dunafer, from still being the most efficient. Regarding the bottom of the ranking we find that, on average, between 2007-2015, the leader appears to be the least efficient in using material inputs and emitting CO_2 emissions in order to produce steel. While studying overallocation profits (see Table 4, Figure 4 and Figure 6) highlights how much EU ETS gave advantage to the leader over 2007-2016, here we observe that ArcelorMittal is the least efficient compared to the other steelmakers. Worse than that, the two most efficient firms,

[10] In 2007, ArcelorMittal's CEO estimated that 46 per cent of its material consumption was provided by its own deposits, and 65 per cent was set up as a 2012 goal (source: Usine Nouvelle (in French); www.usinenouvelle.com/article/arcelormittal-assoit-son-leadership.N23648).

[11] Yearly average nominal price, 62 per cent of Fe content (source: International Monetary Fund)

Voestalpine and ISD Dunafer, are also the ones who have had the lowest cumulated overallocation profits over 2007-2016.

Hence, it seems that by rewarding the least efficient steelmaking firm, who is also the market leader, EU climate policy comes into conflict with EU competition policy.

Regarding the dynamic of the CO_2 efficiency through the Malmquist-Luenberger Productivity Index (MLPI), we assume two technologies for Phase II and Phase III so that we use average input and output values for 2007-2012 and 2013-2015 respectively. Results of the MLPI in Table 6 indicate that Voestalpine is the firm who improved its relative productivity the most between the two periods. This improvement seems to be done through a technical progress ($MLTC > 1$). However, it seems that Riva and SSAB were not able to produce more outputs with lower use of inputs and undesirable outputs. This change fits with results shown in the rankings (Table 5) and appears to be mainly driven by technical efficiency losses ($MLTEC < 1$). We also observe that except for three to four firms, the efficiency change is rather slight since the score is close to one.

We have also extended the MLPI analyses by including the free EUAs as input. Since, they were not provided with the same amount of free EUAs per tonne of CO_2 , this heterogeneous ≪ subsidy ≫ considered here as input makes the ranking different from the one observed in Table 6. The scores obtained in Table 7 reflect how efficient the firm has been relative more efficient in its use of input and CO_2 emissions regarding the number of free EUAs it has been granted in the two periods. The high score for eight of the twelve firms is mostly due to the lower level of free EUAs granted in Phase III. Regarding the number of allowances received, the material and CO_2 intensities, it seems that Tata Steel has been the most efficient in the switch from Phase II to Phase III. In this case the EU ETS' new allocation method might be interpreted as a success. By considering free EUAs as input, we also show that the best relative improvement of efficiency for Voestalpine, does not seem to be mainly driven by the EU ETS. Conversely, the increase in the number of free allowances given to Riva between Phase II and Phase III, combined with its lower efficiency performance compared to others, push it towards the bottom of the ranking. The EU ETS allocation method seems to be in this case, useless.

Table 6: Comparison of efficiency with respect to the EU ETS Phases

Firm	MLPI	MLTEC	MLTC
Voestalpine	1.0736	1.0000	1.0736
Saarstahl	1.0497	1.0385	1.0108
ThyssenKrupp	1.0224	0.9999	1.0225
Salzgitter AG	1.0099	1.0076	1.0022
Tata Steel	1.0072	1.0008	1.0065
US Steel	1.0032	1.0014	1.0018
Dillinger Hütte	1.0026	0.9954	1.0073
Moravia Steel	0.9979	1.0104	0.9875
ArcelorMittal	0.9868	0.9688	1.0186
ISD Dunafer	0.9781	1.0000	0.9781
Riva	0.9384	0.9016	1.0409
SSAB	0.9373	0.9091	1.0310

Table 7: Comparison of efficiency with free EUAs as input

Firm	MLPI	MLTEC	MLTC
Tata Steel	1.3161	1.0819	1.2165
Saarstahl	1.1932	1.0599	1.1258
Moravia Steel	1.1520	1.0456	1.1017
Voestalpine	1.1352	1.0000	1.1352
Dillinger Hütte	1.1305	1.0330	1.0943
US Steel	1.1223	1.0376	1.0816
Salzgitter AG	1.1046	1.0076	1.0962
ArcelorMittal	1.0518	0.9832	1.0698
ThyssenKrupp	1.0224	0.9999	1.0225
ISD Dunafer	0.9770	1.0000	0.9770
SSAB	0.9747	0.9158	1.0643
Riva	0.9384	0.9016	1.0409

6 Conclusion

Sectors subject to international competition still benefit from free allocation of EUAs in Phase III of the EU ETS market. The iron and steel industry is one of them. In addition to account for the highest share of CO_2 emissions from the manufacturing sector, the EU iron and steel industry also appears to be very concentrated. Herein we conduct an in-depth economic analysis of the effect of the EU ETS on this sector through an original installation-level database and a Data Envelopment Analysis. We show how much free allocation generates heterogeneous overallocation profits and mostly benefits to the major steel producers. While in 2007, the leader has, for instance, captured more than 75 per cent of the overall overallocation profit, over the period from 2007-2016, it has cumulated more than twice the amount of overallocation profits of its first competitor. Hence, in this paper we highlight that by protecting the EU steelmakers from international competition, free EUAs might lead to a potential competition distortion within the EU. As a consequence, a trade-off between the EU climate policy and the competition policy arises.

Moreover, it turns out that the market leader is also the least efficient in using iron ore and coking coal (*i.e.* the main inputs to produce steel) to produce crude steel with respect to CO_2 emissions. Here we shed light on the issue related to the way permits are allocated in the iron and steel industry. The switch of methodology that occurs between Phase II and Phase III was supposed to tackle overallocation and reflect the CO_2 intensity of installations through a benchmark. However, our results show that overallocation remains and a strong heterogeneity of CO_2 intensity among steelmakers is observed. Alternative methodologies of allocation are also studied and reveal how the EUAs distribution could have been more stringent. Indeed, a relevant benchmark or an Output-Based Allocation would have exerted stronger pressure to invest in a low carbon process, especially for the less efficient installations.

Regarding the EU ETS revision for Phase 4 (2021-2030) [12], among other adjustments, the benchmark value will be decreased yearly by a coefficient ranging from 0.2 per cent to 1.6 per cent. While for all sectors the value of this coefficient will be determined according

[12] Directive (EU) 2018/410 amends Directive 2003/87/EC to enhance cost-effective emission reductions and low-carbon investments.

to CO_2 emissions in 2016-2017, and will be updated for 2026-2030, the benchmark value for hot metal is already set to be updated yearly by a 0.2 per cent coefficient and will be maintained over the whole period. In addition, the steelmaking industry will still be provided with free EUAs. Hence, we might wonder how the future of the EU ETS can bring optimism in its ability to address the climate change issue in an effective way, at least in regarding the steelmaking industry's CO_2 emissions.

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Appendix A: Methodology of DEA

Static approach: DEA with undesirable outputs

DEA is a non parametric frontier approach that estimates efficiency among comparable entities by solving mathematical programming models (Charnes et al., 1978). Based on the assumption of convexity, DEA compares actual firms to virtual firms that are the weighted combinations of actual firms. Unlike the previous CO_2 intensity ratio (or the inverse form which is the efficiency of steel production by considering CO_2 as the only one input), here we are able to incorporate multiple inputs and outputs. The outcome is known as a technical efficiency which is a score determined for each firm. The performance of the firm is analysed within a group of comparable firms and is evaluated by comparing it to a relative production combination that is achievable in practice. We consider n firms with m inputs and s outputs. Let x_{ij} be the inputs and y_{rj} be the outputs of firm j. The mathematical representation of the score would be as follows:

$$\theta_j = \frac{\sum_{r=1}^{s} u_r \, y_{rj}}{\sum_{i=1}^{m} v_i \, x_{ij}} \qquad j = 1, 2, 3, ...n \tag{4}$$

where θ_j is the efficiency score of the unit j, u_r and v_i are the weights of output r and input i, y_{rj} and x_{ij} are respectively the quantities of output r and input i observed for unit j [13]. DEA has been widely used in economic literature and a large number of extensions have also emerged such as environmental performance evaluation. Regarding the latter, Scheel (2001) introduced various techniques to address the challenge of incorporating environmental externalities in DEA, while Zhou et al. (2008) presented a literature review of the application of DEA in environmental and energy efficiency studies. Basically, we consider that the production of any ≪ desirable ≫ output is accompanied by the joint production of ≪ undesirable ≫ output such as CO_2. To incorporate undesirable outputs in the DEA model, a Directional Distance Function (DDF) technique is used. As explained by Chung et al. (1997) in their article, this approach ≪ solves the problem caused by the joint production of good and bad outputs ≫, which is ignored in traditional DEA models.

Indeed, this allows us to deal with the asymmetric treatment of desirable and undesirable outputs (*i.e.* desirable outputs are maximised while undesirable outputs are minimised) relative to the same amount of inputs. This joint production implies to consider the nulljointness and the weak disposability conditions to the traditional DEA model assumptions. The former means that if a desirable output is produced, some undesirable outputs are generated. The latter means that a reduction of undesirable outputs would be costly, in the sense that either resource must be diverted or production must be cut back (*i.e.* reducing undesirable outputs is considered an opportunity cost).

Formally, the nulljointness condition is described such that: if $(x, y^d, y^u) \in T$ and $y^u = 0$, then $y^d = 0$. The weak disposability assumption is described such that: if $(x, y^d, y^u) \in T$ and $\theta \in [0; 1]$, then $(x, \theta y^d, \theta y^u) \in T$, where we have x, the vector of inputs, y^d the vector of desirable outputs and y^u the vector of undesirable outputs. We also define T as the reference technology that consists of all feasible combinations of inputs x, and outputs

[13] For further details on the general DEA approach see *e.g.* Färe et al. (1994); Cooper et al. (2007)

y^d and y^u. The DDF with undesirable outputs is defined as follows:

$$\overrightarrow{D}_j(x, y^d, y^u) = max\{\theta : (x, y^d, y^u) + (\theta g_x, \theta g_{y^d}, \theta g_{y^u}) \in T\} \quad (5)$$

where the directional vector $g = (g_x, g_{y^d}, g_{y^u})$ determines the direction in which efficiency is measured, such that $g = (g_{y^d}, g_{y^u}) = (y^d, -y^u)$ measuring the most feasible increase of desirable outputs simultaneously to a proportional decrease of undesirable outputs, with respect to constant quantity of inputs (Chung et al. (1997); Dubrocard and Prombo (2012)). Hence the DDF becomes:

$$\overrightarrow{D}_j(x, y^d, y^u) = max\{\theta : (x, y^d, y^u) + (\theta g_{y^d}, -\theta g_{y^u}) \in T\} \quad (6)$$

The value of the directional efficiency measure $\overrightarrow{D}_j$, represents the distance between observation (y^d, y^u) and a point $(y^d + \theta g_{y^d}, y^u - \theta g_{y^u})$ on the production frontier. It projects the value observed for firm j along the pre-assigned direction corresponding to the output vector $g_y = (y^d, y^u)$. Following the developments of DEA model with undesirable outputs made by Aparicio et al. (2015), Alvarez et al. (2016) defines the following programme to compute the efficiency score for each unit j:

$$\begin{aligned} \overrightarrow{D}_j(x_j, y^d_j, y^u_j) = \quad & \max_{\theta,\lambda} \quad \theta_j \\ & \text{subject to} \\ & X\lambda \leq x_j \\ & Y^d\lambda \geq y^d_j + \theta y^d_j \\ & Y^u\lambda \leq y^u_j - \theta y^u_j \\ & max\{y^u_i\} \geq y^u_j - \theta y^u_j \\ & \lambda \geq 0 \end{aligned} \quad (7)$$

where $j = 1, 2, ..., n$ is the observed firm, $X = (x_1, x_2, ..., x_m)$ and $Y = (y_1, y_2, ..., y_s)$ are the input and output vectors of m and s dimension respectively, $\lambda = (\lambda_1....\lambda_n)$ is a semi-positive vector. Hence, considering undesirable outputs, we have $y = (y^d, y^u)$. The optimal solution $0 \leq \theta_i \leq 1$ is computed for each firm. If $\theta_i = 0$, the firm is considered as efficient since there is no difference between the observed values and the efficient production frontier. A value of $\theta_i > 0$ shows inefficiency meaning that the estimated values $(\lambda X, \lambda Y^d, \lambda Y^u)$ outperform the observed values (x_j, y^d_j, y^u_j).

Dynamic approach: the Malmquist-Luenberger Productivity Index

Based on the previous DDF approach, Chung et al. (1997) developed the Malmquist Luenberger index. Unlike its static counterpart based on cross-sectional data, the non parametric Malmquist-Luenberger Productivity Index (hereafter ≪ MLPI ≫) uses time-series data and also includes undesirable outputs. This index measures the change in productivity by comparing its relative efficiency with respect to reference technologies corresponding to two different time periods. Thus, we are able to dissociate efficiency change and technical change. The former is called ≪ the catch-up effect ≫. It refers to the technical efficiency with respect to the two periods (hereafter ≪ MLTEC ≫). The latter corresponds to a ≪ frontier-shift effect ≫ which is the change in the reference frontier between both periods (hereafter « MLTC »).

We consider $(x_j^t, y_j^{t,d}, y_j^{t,u})$ observed in $t = 1, 2$, while $\theta^{1,1}$ and $\theta^{2,2}$ are the efficiency scores of period one and two computed from program (7). The first superscript is the time period and the second superscript is the reference technology. We also define the intertemporal score $\theta^{2,1}$ assessing the observations of period two $(x_j^2, y_j^{2,d}, y_j^{2,u})$ with respect to technology in period one $(X^1, Y^{1,d}, Y^{2,u})$. The programme becomes:

$$\begin{aligned}
\overrightarrow{D}_j(x_j^2, y_j^{2,d}, y_j^{2,u}) = \quad & \max_{\theta,\lambda} \quad \theta_j^{2,1} \\
& \text{subject to} \\
& X^1\lambda \leq x_j^2 \\
& Y^{1,d}\lambda \geq y_j^{2,d} + \theta y_j^{2,d} \\
& Y^{1,u}\lambda \leq y_j^{2,u} - \theta y_j^{2,u} \\
& max\{y_i^{t,u}\} \geq y_j^{2,u} - \theta y_j^{2,u} \\
& \lambda \geq 0
\end{aligned} \tag{8}$$

An equivalent program is used to compute $\theta^{1,2}$ so that given a sequence of two years, we can define the MLPI as [14]:

$$MLPI = \overbrace{(1 + \theta^{1,1}/1 + \theta^{2,2})}^{MLTEC} \times \underbrace{(1 + \theta^{2,2}/1 + \theta^{2,1}) \times (1 + \theta^{1,2}/1 + \theta^{1,1})]^{\frac{1}{2}}}_{MLTC}$$

where the first component is the change in technical efficiency and the second is the technical change. If $MLPI > 1$, the unit is able to produce more desirable output with less undesirable output, while $MLPI = 1$ means the productivity remains unchanged, and $MLPI < 1$ captures a productivity decline.

[14] For further details see Alvarez et al. (2016)

Appendix B: DEA results

Thanks to the linear model defined in (7) and based on our cross sectional data, we can compute the relative CO_2 emission efficiency score. Results are given in the following Table:

Table 8: The static CO_2 emission performance scores of the steelmaking firms (2007-2015)

Firm	Average	2007	2008	2009	2010	2011	2012	2013	2014	2015
Voestalpine	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ISD Dunafer	0.003	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.030	0.000
Salzgitter AG	0.031	0.000	0.013	0.068	0.047	0.029	0.044	0.025	0.009	0.042
Moravia Steel	0.037	0.000	0.000	0.000	0.078	0.086	0.061	0.037	0.000	0.068
SSAB	0.073	0.022	0.077	0.000	0.000	0.088	0.104	0.090	0.057	0.218
US Steel	0.081	0.090	0.136	0.052	0.022	0.117	0.113	0.000	0.065	0.131
Tata Steel	0.089	0.000	0.084	0.000	0.155	0.274	0.041	0.185	0.013	0.052
ThyssenKrupp	0.090	0.076	0.054	0.115	0.083	0.096	0.131	0.088	0.112	0.056
Riva	0.101	0.021	0.121	0.047	0.007	0.134	0.100	0.201	0.114	0.166
Dillinger Hütte	0.116	0.187	0.132	0.069	0.080	0.082	0.156	0.111	0.083	0.148
Saarstahl	0.119	0.119	0.130	0.211	0.096	0.106	0.171	0.078	0.069	0.087
ArcelorMittal	0.128	0.154	0.239	0.032	0.094	0.084	0.127	0.129	0.116	0.179