N°2021 - 06 • JULY 2021

WORKING PAPER

Technological progress and carbon price formation : an analysis of EU-ETS plants

Marc BAUDRY [1,2], Anouk FAURE [1,2*]*

This study investigates the nature of technological progress in six manufacturing industries covered under the EU-ETS, plus the power sector, and its effect on carbon price formation using marginal abatement cost curves. We adopt a technological frontier framework, which we calibrate to input and output data at the plant level from 2013 to 2017, with a directional distance function approach. Our results reveal that most of the time, technological progress resulted in inflating baseline emissions, despite decreasing the carbon intensity of production. In our sample industries, technological progress therefore leads to increase abatement efforts, raising the equilibrium price of carbon.

JEL CODES : Q55 ; O33; D24; L6.

1* EconomiX, Paris-Nanterre University (UPL), France
2* Climate Economics Chair 75002 Paris, France

Corresponding author email address: marc.baudry@ParisNanterre.fr

KEYWORDS

Directed technological change | Frontier analysis | EU-ETS

1 Introduction

The role of technological progress in a pollution-constrained world has mostly been studied through the prism of induced technological change. First developed by J.R. Hicks in the context of the labor market, it states that technological progress will benefit more some inputs than others, according to their relative prices. In his words, *"A change in the relative prices of the factors of production is itself a spur to invention, and to invention of a particular kind - directed to economising the use of a factor which has become relatively expensive"* (Hicks, 1932). Assuming factor-augmenting technologies, Acemoglu (1998, 2002, 2007) then formalized that market mechanisms can, by altering input prices, steer technological change in favor of specific technologies in turn. Economists being increasingly concerned with environmental problems like global warming, it was soon showed that an environmental policy can also influence the direction of technological change towards cleaner inputs (Acemoglu et al., 2012) or low carbon innovation (Grubb et al., 1994; Goulder & Schneider, 1999; Gerlagh et al., 2009), with consequences on the design of CO_2 abatement policies (Goulder & Mathai, 2000).

Most of the above mentioned literature has focused on the technological consequences of CO_2 pricing. However, induced technological change can be approached in a broader sense, as suggested by Porter's hypothesis. The initial version of Porter's hypothesis (Porter & Van der Linde, 1995) sheds light on how environmental policy, in a broad sense, is likely to push companies to reduce technical or organizational inefficiencies of which they would not be aware in the absence of this policy. The two authors then extend their analysis by taking into account innovation strategies aimed at circumventing the additional cost of environmental policy and by examining the overall incidence on firm's performance. Empirical analysis of this extended Porter's hypothesis have either consider the incidence of all environmental levies in total environmental exploitation costs (Van Leeuwen & Mohnen, 2017) or explicitly control for the impact of environmental standards in parallel to the impact of prices (Aghion et al., 2016). Another piece of literature is concerned with the fact that it is relative prices that matter in guiding technological change. Thus, Popp et al. (2020) interpret the sharp drop in patent filings covering clean technologies over the last decade as, at least in part, the consequence of the fall in the price of fossil fuels. It emerges from all of these works that environmental policy instruments probably influence the direction of technological change, but that their effect is interwoven with many other influences that make their assessment complex.

This paper specifically put the emphasis on the interplay between carbon markets and technological change. Due to low carbon prices until the late third trading period (2013-2020), little attention has been paid to the response of technological progress to the European Union Emissions Trading Scheme (EU-ETS). A few studies analyzing the causal impact of the EU-ETS on technological advances did so with a focus on low-carbon patenting and R&D expenditure (Borghesi et al., 2015; Calel & Dechezleprêtre, 2016; Calel, 2020). The specificity of carbon markets for the study of oriented technological change lies in the fact that it is not directly the price that is regulated but the supply of allowances. The direction of technical progress therefore crucially depends on two elements. The first element is the link between the supply of allowances on the one hand and their market price on the other hand. The existence of transaction costs (Baudry et al., 2021) and the dynamic nature of the market (Quemin & Trotignon, 2021) are indeed likely to disrupt the theoretical link between the two. The second element is that the price of allowances does not only depend on the quantity of allowances allocated but also on multiple other factors. The much studied price slump that occurred in the second trading period (2008-2012) has mainly been attributed to a supply imbalance indeed (De Perthuis & Trotignon, 2014; Ellerman et al., 2015), and econometric studies identified energy prices (Creti et al., 2012; Koch et al., 2014), renewable energy supply and weather variation (Alberola et al., 2008; Rickels et al., 2015), political events and announcements (Hitzemann et al., 2015; Koch et al., 2016), banking of allowances (Hintermann, 2010), or hedging and speculation (Friedrich et al., 2020; Tietjen et al., 2020) to be the main carbon price drivers.[1] Nevertheless, the feedback effect of technological progress on carbon price formation and policy design has never been considered, to our knowledge, in the theoretical and empirical literature on the EU-ETS.

In the context of the EU-ETS, we argue that half of the picture could have been missed, by overlooking the role of technological progress in carbon price formation. By contrast to Acemoglu's model and the subsequent literature, we do not make any preliminary assumption about the nature of technological progress. More precisely, we go beyond the dichotomous view resulting from the explicit distinction between intrinsically "green" and intrinsically "gray" inputs. By implicitly considering that any input can be more or less "green" or "gray", we introduce the idea of a continuum of possible directions of technological change. We therefore consider that any improvements of regulated plants' total factor productivity can affect the carbon market's fundamentals, namely marginal costs of abatement, and investigate their effect on carbon price formation. The paper proceeds in three structuring steps.

First, and on the basis of the technological frontier framework developed by Shephard (1970),

[1] A comprehensive review can be found in Hintermann et al. (2016).

we develop a measure of technological progress experienced by plants over time. Departing from a binary, clean *versus* dirty technological adoption, this approach enables us to characterize technological progress without any presupposition about its nature, and information about the price of production factors. As a characterizing criterion, we define *non-directed* technological progress to increase both carbon intensity of production and baseline emissions under $laisserfaire$ conditions. By contrast, technological progress is referred to as *directed* when the carbon intensity of production decreases. As sub-cases, *strongly* (*weakly*) *directed* technological progress results in decreasing (increasing) baseline emissions. However, implementing these definitions to characterize technological change requires measuring carbon intensity in an relevant manner. Indeed, the carbon intensity on which these definitions are based is not that observed but that which would prevail in the absence of any policy influencing it. In other words, it is the carbon intensity intrinsically characterizing the technology in place that must be used. This is done using a directional distance function method. (Chung et al., 1997) We focus on six manufacturing industries covered under the EU-ETS over the 2013-2017 period, plus the power sector, and calibrate industry technological frontiers on plant input and output data from the European Union Transaction Log[2] and the Amadeus[3] databases. Our results reveal that on average, technological progress mostly led to inflate plants' baseline, i.e. $laisserfaire$ emissions, and lower the carbon intensity of production, which we qualify as *weakly directed*. Therefore, we find that plants primarily seek total factor productivity gains despite the environmental regulation, putting in perspective the induced technological change literature.

Second, calibrated technological frontiers enable us to compute annual, parametric marginal abatement cost (MAC) curves at the industry level, based on a revenue-maximization program. Therefore, we contribute to the empirical literature on MAC estimation in the EU-ETS, which mainly relies on the outputs of macroeconomic models (Landis, 2015), or *ad-hoc* calibration methods (Baudry et al., 2021; Beck & Kruse-Andersen, 2018; Quemin & Trotignon, 2019). By contrast to these methods, our approach to estimate MAC curves requires little assumptions about the structure of the markets for products and pollutants, and has modest data requirements. Consequently, we argue that it could provide a practical alternative to the benchmarking procedure, currently used to determine the size of plants' free permit endowment in the EU-ETS. The analysis of MAC curves' then reveals great differences in magnitude between high and low carbon intensity industries. Specifically, a realistic price of carbon would trigger a much greater abatement effort in highly carbon-intensive industries

[2]The emissions and transactions electronic registry of the EU-ETS

[3]From Bureau Van Dijk, which records financial plant data

that in low carbon intensity ones. Furthermore, the nature of technological progress greatly affects the amount of abatement that can be realized at a given price, because of its effect on aggregate baseline emissions. Specifically, baseline-inflating (resp. deflating) technological progress contributes to increase (resp. decrease) emissions reductions.

Third, numerical MAC curves enable us to analyze the transmission of technological progress to the annual market price of carbon from 2013 to 2017. More precisely, we compute equilibrium carbon prices under 2013's conditions, had technological progress observed in later years happened. Price deviations from their 2013 level can then be attributed to technological progress. Thus, we use permit allocation data from the EUTL to compute the permit deficit of production sites. Interestingly, and since baseline-inflating technological progress is dominant in our samples, it results in increasing the market clearing price by up to 34€/tCO_2 over time. The analysis of industries' net permit demand in equilibrium also reveals significant permit transfers from low to high carbon-intensity industries. Consequently, our results suggest that technological progress which is not *strongly directed* by nature tightens the effective emissions constraint, and increases the financial burden of highly carbon intensive industries, which has policy implications.

The remainder is organized as follows: Section 2 presents the technological frontier framework and our modeling approach of marginal abatement cost curves, Section 3 presents the data and the directional distance function calibration method, Section 4 conducts an efficiency analysis of selected industries and discusses the dynamics of marginal abatement cost curves, Section 5 presents the market equilibrium and analyzes the impact of technological change, and Section 6 discusses policy implications.

2 Theoretical framework

2.1 Technological frontiers

In this study, the production of manufacturing goods is considered to be a multi-input, multi-output process, involving the production of both good (e.g. cement) and bad (e.g. greenhouse gases) outputs. First introduced by Shephard (1970), and generalized by Chambers et al. (1998) to accommodate a multi-output framework, the relationship between inputs and outputs may be characterized by a production set containing all combinations of goods and bads which can be obtained from a given set of inputs (Coelli et al., 2005). Considering a vector x of inputs, a vector y of good outputs (i.e. production) and a vector b of bad outputs (i.e. pollutants), a production technology set $P(x)$ of a plant can be defined as

$$P(x) = \{(y, b) : x \text{ can produce } (y, b)\}$$

According to classical micro-economic assumptions, the representation of $P(x)$ exhibits the following properties

- production requires a positive level of inputs : $P(0) = (0, 0)$.
- the size of the set cannot decrease if more inputs are used: $x' \geq x$ implies $P(x) \subseteq P(x')$.
- desirable outputs can be disposed at no cost: $y' \leq y$ implies $(y', b) \in P(x)$.
- good and bad outputs are jointly produced: if $b = 0$, $y = 0$.
- bad outputs cannot be freely disposed: $0 \leq \theta \leq 1$ leads to $(\theta y, \theta b) \in P(x)$.

The production set is closed by a so-called technological frontier, which reflects the current state of technology of a producing plant. Technological progress may then be characterized by an expansion of the technological frontier, i.e. an increase in total factor productivity, keeping inputs constant.

In the case of a single good and bad output, Figure 1 illustrates the technological structure of a plant which experiences technological progress at $t + 1$ (dashed curve). Although this approach enables us to represent a wide range of improvements in (b, y) combinations, we select a criterion to qualify the nature of technological progress for the purpose of this study. We choose to base this criterion on changes in the carbon intensity of production, rather than in the absolute level of pollution b, for its greater flexibility and realism. Carbon intensity is a concept widely used in the literature dealing with environmental performance, especially at the macroeconomic level. At first glance, because it is defined as the ratio between carbon emissions and output, it is easy to calculate and plays a crucial role when identifying the factors that contribute to the total level of emissions in Kaya's identity (Kaya, 1989). This simplicity is however misleading because it does not provide information on how the observed level of carbon intensity is obtained. The same observed level of carbon intensity can result from very different contexts indeed. It can result from the use of inherently environmentally efficient technology without a restrictive policy to control carbon emissions. Conversely, it can be obtained under the decisive effect of a restrictive environmental policy and despite a technology that is not efficient in terms of carbon emissions. The measurement of carbon intensity relevant to assess the direction taken by technical progress must be based exclusively on technological aspects and must therefore disregard short-term emission reductions induced by environmental policies. We are therefore concerned with the direction of the change in the carbon intensity of production due to technological progress at maximum y, i.e. with no constraints on pollution. Graphically, this corresponds to comparing positions of radius of the (b, y) orthant passing through the top of the technological frontiers at t and $t + 1$. Indeed, as detailed *infra*, the summit of a technological frontier corresponds to the optimal, revenue-maximizing choice under $laisserfaire$ conditions, and thus characterizes the carbon intensity (i.e. the slope of the radius) associated to the technology in the absence of any environmental policy.

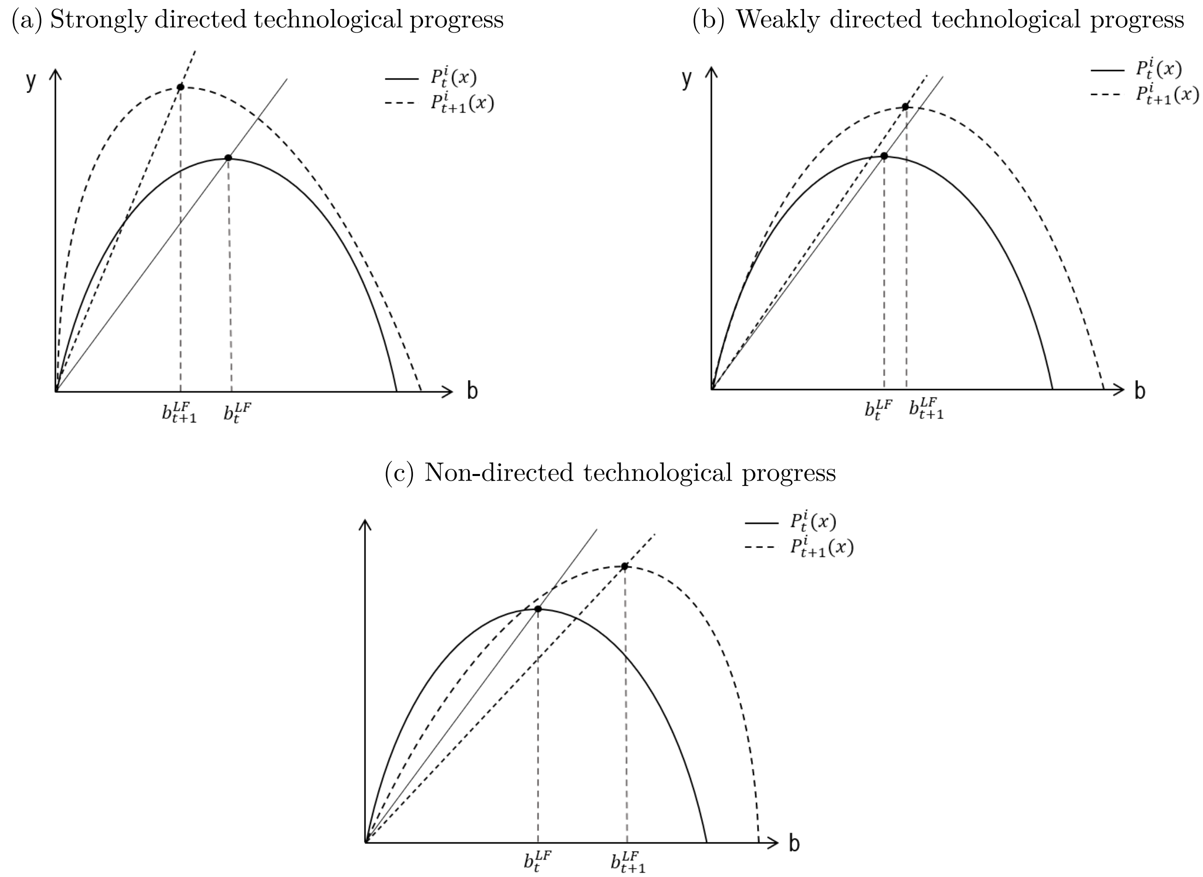
Figure 1 illustrates the three natures of technological progress. In panel (C), technological progress increases both the carbon intensity of production and baseline emissions, which we refer to as *non-directed* technological progress. By contrast, panel (A) and (B) characterize *directed*, i.e. carbon-intensity decreasing technological progress. Note that, although *non-directed* technological progress unequivocally results in increasing the $laisserfaire$ pollution level b^{LF}, the case of *directed* technological progress is not straightforward. The latter can lead to either decrease or increase baseline emissions indeed. To clarify this difference, we therefore distinct *strongly* and *weakly directed* technological progress, which respectively result in decreasing (panel (A)) or increasing (panel B) the level of $laisserfaire$ pollution b^{LF}. In practice, an example of *strongly directed* technological change in the cement industry can be the switch to a waste-heat recovery system,[4] which enables to increase the productivity of energy, thus decreasing the carbon-intensity of production. By contrast, the replacement of an old limestone grinder can avoid raw material losses and lead to increase output-per-capita, without changing the carbon intensity of cement. In our framework, this corresponds to *weakly directed* technological change.

The nature of technological progress being defined at the *micro*, plant level, measuring it requires to move to a *meso* level of analysis. Indeed, a technological frontier can only be quantified with multiple points. Therefore, and conforming to the theoretical framework, we have to consider a set of plants sharing the same technology in order to characterize an industry technological frontier, which can be estimated as detailed in Section 3.

Letting two plants 1 and 2 use the same quantity of inputs x, the production sets $P_t^1(x)$ and $P_t^2(x)$ can be represented in the bi-dimensional space (b, y), as in Figure 2. Their

[4] High-performing coolers make it possible to recover the excess heat during the clinker cooking process for electricity generation.

Figure 1: Nature of technological progress

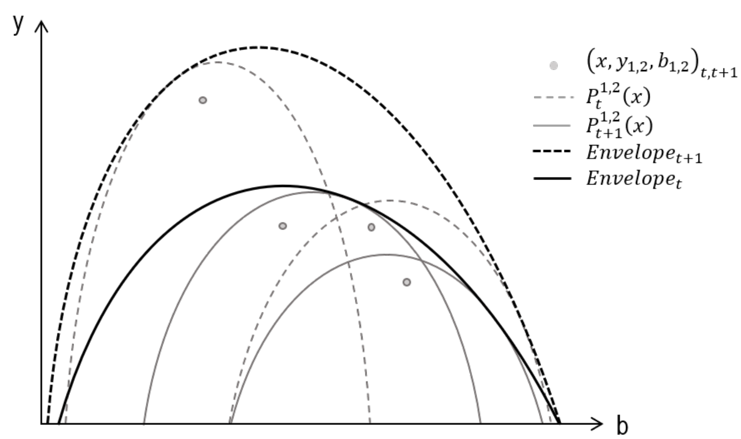


Note: $P_t^i(x)$ and $P_{t+1}^i(x)$ denote the technological frontier of plant i at t and $t+1$, respectively. b_t^{LF} and b_{t+1}^{LF} denote $laisserfaire$ emissions at t and $t+1$.

respective combination of good and bad outputs correspond to the empty and full grey dots. First, note that plants operate below their technological frontier in our representation, which reveals some scope for technical efficiency improvements, namely production technique enhancements (e.g. plant management, organization of the production line) given the state of technology and set of inputs. The reduction in emissions, with unchanged production, which can be obtained by absorbing these inefficiencies reveals what is sometimes referred to in the literature as being cost-free abatement. This level of abatement is obtained in Figure 2 by moving horizontally to the border. However, it is possible to absorb the same inefficiency by reducing emissions while increasing production, i.e. by moving towards the border not horizontally but in a direction oriented to the left and upwards of Figure 2. This configuration typically corresponds to the initial idea of Porter's hypothesis, namely that the reduction of inefficiencies can reconcile improvement of environmental performance and improvement of the economic performance of the plant. Second, both plants experience technological progress between t and $t+1$, as their production sets $P_t^1(x)$ and $P_t^2(x)$ expands over-time. Consequently, the new production technology enables them to make more out of an unchanged set of inputs, in terms of quantity of desirable output y. Furthermore, plant 2's technology is dominated by plant 1's despite technological progress. For any b indeed, the maximum production level y is greater at both t and $t+1$ for plant 1. Note that technological progress, characterized by a displacement of the frontier, is independent from technical efficiency which relates to the distance to the frontier.

In the same way as at the plant level, the three natures of technological progress (i.e *strongly* or *weakly directed*, and *non-directed*) can then be characterized at the industry level. To do so, we define an envelope curve which embodies plants' production sets in a single, industry super-set (plain and dashed black curves in Figure 2). The envelope curve at $t+1$ captures all technological changes that occurred at the plant level in turn. Comparing carbon intensities at the top of the envelope curve at t and $t+1$ then enables us to characterize the type of technological progress experienced in aggregate. In the illustration, technological change at the industry level is *strongly directed*.

Figure 2: Plant and industry technological frontiers



Note: Representation at t and $t+1$ of the production sets $P(x)$ of two producing plants producing one desirable good and one pollutant, y and b, and using x inputs.

2.2 Marginal abatement cost curves

Having characterized technological progress, we can now compute the marginal abatement cost (MAC) of plants that are subject to a pollution constraint. We define MAC in line with textbook environmental economics, which state profit-maximizing producers trade-off sales revenue from the production of goods with the cost of complying with the environmental regulation (Tietenberg & Lewis, 2016). Our approach thus substantially differs from that of expert based MAC curves like McKinsey's (McKinsey, 2009), who analyze the cost merit order of abatement options relying on the adoption of low-carbon technologies or energy-efficiency measures. More precisely, the technological frontier method enables us to consider two ways of carry out emissions reductions visible on Figure 2. On the one hand, a plant can abate by reducing its production level y, thus leading to a financial sacrifice. On the other hand, it can switch to another, 'cleaner' technology, as if plant 1 adopted plant 2's technology (plain grey lines on Figure 2). Such costs of technological adoption corresponds to abatement costs *a la* McKinsey. Yet, note that *micro* technological changes are hidden in our *meso* analysis.

More precisely, in presence of an individual cap on emissions, a plant's cost of compliance is equivalent to the decrease in sales revenue due to required emissions reductions. The corresponding abatement cost may then be measured by comparison to the *laisser-faire* situation. Thus, MAC can be defined as the foregone revenue associated with the tightening of the pollution constraint by one additional unit. When the environmental regulation takes the form of a market based instrument, such as an emissions trading scheme or a tax on emissions, MAC directly guide plants' production choices. For instance, polluting plants will optimally emit until the marginal abatement effort is as costly as the permit price on the emissions trading scheme, or as the unitary tax.

Formally, the objective of a polluting plant i selling its production y on the goods market is

$$\max_{y,b} \; R_i = p_y y_i \quad \text{s.t} \quad (b_i, y_i) \in P_i(x) \; , \; b_i \leq \bar{b_i}$$

where revenue-generating production necessarily involves a polluting by-product b. All plants are assumed to be price takers on the goods market. Besides, inputs are fixed according to the technological frontier framework presented in Section 2.

Under $laisserfaire$ conditions, $\bar{b}_i$ does not bind, hence the producer faces an unconstrained revenue maximization problem. The solution corresponds to the level b_i^{LF}, also referred to as baseline emissions, which satisfies $f_i'(b) = 0$ where f_i denotes the functional expression of the technological frontier in the (b, y) space. Graphically, the (y_i^{LF}, b_i^{LF}) coordinates correspond to the top of the technological frontier (see Figure 3). In presence of an environmental regulation however, $b \leq \bar{b}$ is binding. The optimal level of abatement of plant i can thus be defined as $a_i = b_i^{LF} - b_i^\star$, with $b_i^\star$ the solution of the constrained maximization program. For any pollution constraint, the abatement cost then corresponds to the foregone revenue, or $p_y \times (f_i(b_i^{LF}) - f_i(b_i^{LF} - a_i))$. The plant's MAC can be computed as the derivative of the above: $p_y \times f_i'(b_i^{LF} - a_i)$.

Next, to obtain an industry MAC curve mapping pollution prices against abatement efforts, first denote plant i's MAC $MC_i(a_i) = p_y \times f_i'(b_i^{LF} - a_i)$ to obtain $a_i = b_i^{LF} - (f_i'^{-1})(MC_i/p_y)$. The last expression gives, for plant i, the quantity of emissions reduced relative to baseline emissions at any implicit pollution price. At the industry level I, the total abatement effort at any price then corresponds to the horizontal sum of a over plants:

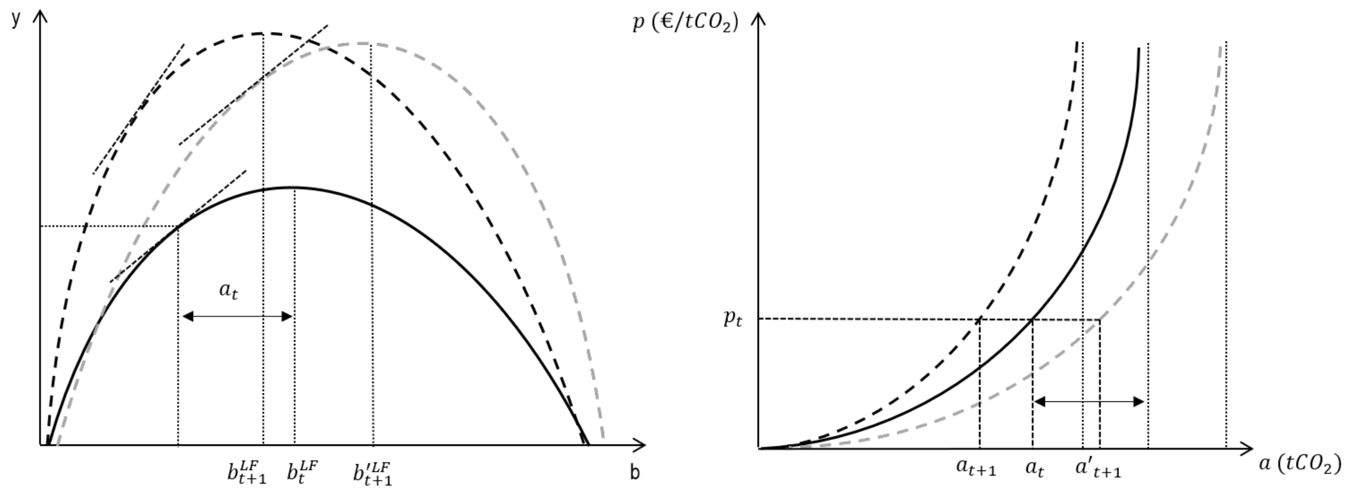
$$a_I = \sum_{i \in I} \left(b_i^{LF} - f_i'^{-1}(MC_i(a_i)/p_y) \right)$$

Figure 3 illustrates the correspondence between technological frontiers and MAC curves. Although plants can experience some technical inefficiency in practice, revenue maximization necessarily results in technically efficient production decisions. In turn, MAC are computed along the technological frontier, meaning that zero-cost abatement measures are non-existent.

The left part of Figure 3 illustrates an industry's technological frontier $f(b)$ before technological progress occurs (plain black line). Starting from baseline emissions b_t^{LF}, any level of pollution constraint matches an implicit price of pollution. Graphically, and for an arbitrary abatement effort a_t, the corresponding MAC reflects the absolute value of the slope of the tangent to the technological frontier. Besides, the asymptote of MAC curves shown in Figure 3 corresponds to the maximum abatement that can be done at the industry level. Note indeed that $laisserfaire$ conditions correspond to the intercept of the MAC curve. Then, as pollution control strengthens, the foregone revenue from production increases and tends to infinity as emissions tend to zero.

It becomes clear in Figure 3 that the shape of MAC curves is inherently linked to that of technological frontiers, and the nature of technological progress in turn. Specifically, *non-directed* and *weakly directed* technological progress shifts the MAC's asymptote to the right as baseline emissions increase, which will result in lowering the MAC curve (dashed grey line). By contrast, *strongly directed* technological progress shift the asymptote to the left, which contributes to increasing MAC (dashed black line). Changes in the curvature of the technological frontier due to technological progress will also affect the slope of MAC curve, in no clear direction yet.

Figure 3: Technological change and MAC curves



3 Empirical Approach

In this Section, we apply our theoretical framework to manufacturing industries covered under the EU-ETS during the early third trading period (2013-17), and analyze the effect of technological progress on industries' MAC curves.

3.1 Data

First, we collect input, production and pollution data at the plant level to estimate industries' technological frontiers, conforming to the theoretical framework presented in section 2. Two databases, paired by plant names (*"account holder name"*) are used. First, the Amadeus database from Bureau van Dijk documents financial information on European production sites, including annual accounts, financial ratios, industry and ownership. Amadeus data covers the 2009-2017 period. Second, the European Union Transaction Log (EUTL) records the trading and compliance activity of plants covered under the EU-ETS, including transactions, annual allocation and reconciliation of permits. The EUTL covers the same years as Amadeus, yet the transition from the second (2008-2012) to third (2013-2020) trading period led to discrepancies in the reporting of emissions data, as many production sites changed account holder name. Therefore, we choose 2013 as the initial date for our panels, which coincides with the start of Phase 3 of the EU-ETS. We obtain balanced panels binned in seven 4-digit NACE rev. 2 code,[5] from 2013 to 2017. Table 1 provides an overview of selected

[5] We chose to merge NACE 20.12, 20.13 and 20.14 under a more general «Chemicals» industry, due to data scarcity at the 4-digit level. We checked that three sub-industries present similar carbon intensities.

industries, most of which are manufacturing of mineral products and basic metals, plus the power sector.

Table 1: Industry description

Industry	NACE rev. 2	Activity description
Baked clay	23.32	Manufacture of bricks, tiles and construction products, in baked clay
Cement	23.51	Manufacture of clinkers and hydraulic cements, including Portland, aluminous cement, slag cement and superphosphate cements
Chemicals	20.1(2-3-4)	Manufacture of organic and inorganic basic chemicals, dyes and pigments
Electricity	35.11	Production of electricity, including operation of generation facilities that produce electric energy
Metallurgy	24.1	Manufacture of basic iron and steel and of ferro-alloys
Paper	17.12	Manufacture of paper and paperboard
Plaster	23.52	Manufacture of plasters of calcined gypsum or calcined sulphate, and manufacture of quicklime, slacked lime and hydraulic lime

Using the practical guidance of Coelli et al. (2005), we select capital, labor and energy as inputs, and production and CO_2 emissions as desirable and undesirable outputs. More precisely, capital is measured by the value of tangible assets, labor by total payroll and energy by the value of purchased raw materials and other supplies. Production is measured by sales revenues and pollution by verified CO_2 emissions. Besides, to correct inflation variations over-time and price-level differences across countries, we deflate the data with an inflation index and convert it to purchasing power parity.[6] Table 2 reports descriptive statistics of the resulting samples, and Figure 6 in the appendix shows the dynamics of variables over 2013-17. Note that data belonging to a NACE 4-digit industry can be split in two or three sub-samples according to carbon intensity, measured by the average emissions-to-production ratio of plants over all years (see for instance baked clay products, metallurgy and paper production). This first ensures that samples have a similar 20-to-30 observations. Having homogeneous samples, in terms of economic activity, is indeed a central point of the technological frontier calibration presented in Section 3.2. Second, it enables us to further analyze whether the carbon intensity of production affects the nature of technological progress.

On average for the selected production sites, Table 2 shows that cement and power sectors are the biggest emitters, with more than 400ktCO_2 annually. Manufacturers of mineral product

[6] https://appsso.eurostat.ec.europa.eu/nui/submitViewTableAction.do

(NACE 23) also have the highest carbon intensity.[7] Moreover, computing the capital intensity of production sites, i.e. the capital-to-production ratio, reveals that on average, plants that have a higher carbon intensity of production also tend to be more capital intensive.[8] We could therefore expect a greater potential for *directed* technological progress in those industries. Surprisingly, cement manufacturers presents a low capital intensity despite being highly carbon intensive. This could be due to the use of carbon inputs, which is not reflected here, or a low valuation of tangible assets.

Table 2: Data overview

Industry (Nace 2)	#Obs	Carbon intensity	Capital intensity	Emissions	Production	Capital	Energy	Labor
Baked clay (23.32)	28	0.4 (0.7)	0.6 (0.7)	18,035 (14,541)	42,437 (20,536)	26,762 (14,370)	15,342 (5,765)	10,376 (3,733)
	29	3.6 (4.1)	1.2 (0.7)	11,082 (7,756)	3,012 (1,886)	3,541 (1,467)	1,198 (670)	638 (442)
Cement (23.51)	26	5.1 (6.8)	0.6 (0.7)	626,319 (56,794)	121,636 (83,456)	75,303 (62,588)	38,167 (29,623)	22,268 (13,580)
Chemicals (20.1)	20	0.3 (0.4)	0.3 (0.3)	156,674 (87,645)	578,601 (195,624)	160,064 (78,383)	328,671 (73,810)	60,224 (19,944)
Electricity (35.11)	22	1.1 (0.2)	0.9 (1.2)	420,341 (49,204)	379,998 (229,560)	356,290 (269,279)	200,814 (116,953)	37,284 (18,726)
Metallurgy (24.1)	28	0.1 (0.1)	0.2 (0.2)	68,845 (54,413)	574,689 (420,228)	138,704 (95,780)	395,098 (281,465)	55,397 (40,344)
	25	0.5 (0.6)	0.4 (0.4)	116,663 (91,921)	232,382 (134,096)	78,202 (49,529)	148,902 (75,231)	22,532 (15,432)
Paper (17.12)	25	0.1 (0.1)	0.2 (0.2)	18,659 (12,863)	138,541 (109,382)	33,715 (26,437)	69,946 (50,405)	19,988 (14,778)
	24	0.5 (0.4)	0.2 (0.9)	49,887 (26,564)	104,520 (69,471)	24,191 (20,540)	64,404 (31,181)	12,816 (7,639)
	25	1.1 (0.9)	0.3 (0.4)	69,714 (44,097)	63,828 (47,870)	22,034 (17,566)	33,898 (23,029)	7,392 (4,826)
Plaster (23.52)	27	2.8 (4.6)	0.7 (0.5)	122,911 (81,940)	43,651 (17,475)	32,705 (8,425)	14,396 (4,662)	6,716 (2,352)

Note: Indicated values are means over years and plants. Production and inputs are expressed in k€. Emissions are expressed in tCO_2. The column #Obs indicates the number of production sites per cross-section. Medians are reported in brackets.

[7] Recall that carbon intensity is usually expressed in tCO_2/unit of production, yet it is expressed in tCO_2/k€ in our case, as our data is in constant € corrected with purchasing power parity.

[8] Capital intensity is lower than one in most cases, meaning that the market value of production is superior to that of tangible assets on average. This is consistent with usual Fixed Asset Turnover Ratios.

3.2 Directional distance functions

Next, we employ a directional distance function approach to calibrate industries' technological frontiers over the 2013-17 period. First introduced by Chung et al. (1997), the general idea behind directional distance function is to minimize the distance between observed plants and their technological frontier. It is then possible to identify plants that are technically efficient (namely, make the most of inputs given the state of technology) and those for which technical efficiency improvements are possible. As such, directional distance functions have been widely used as management tools to benchmark decision-making-units (e.g. companies' services, production plants etc.). This approach has several methodological advantages. First, it does not require any assumption about the economic or regulatory environment (Wei et al., 2013; Zhou et al., 2014). Second, data requirements are modest in directional distance function analysis (only input and output quantities or values are needed at the production unit level), which facilitates its implementation and reproduction. Therefore, the directional distance function method has allowed to develop a measure of technical efficiency and total factor productivity growth that does not rely on the price of production factors.

Formally, an individual directional distance function is defined as[9]

$$\vec{D}_i(x, y, b; g_y, -g_b) = \sup\{\beta : (y + \beta g_y, b - \beta g_b) \in P(x)\} \tag{1}$$

where β represents the maximum expansion (resp. contraction) in the good (resp. bad) outputs allowed by the plants' technological state along some direction vector $g = (g_y, -g_b)$. Graphically, the directional distance function projects each decision-making-unit onto the boundary of the production set (or frontier). The inefficiency score β is then null for technically efficient plants, which lie on the technological frontier, while plants for which technical efficiency improvements are possible present a positive distance.

For the purpose of this study, the specification of the directional distance function must fulfill two criteria. First, it must be parametric since we need a technological frontier that is twice differentiable for our analysis of marginal abatement cost curves. We then exclude the Data Envelopment Analysis method, which consists in evaluating plants' technical efficiency scores β with a non-parametric approach, for it would result in a piece-wise representation of MAC curves. Second, the directional distance function's functional form must allow for linear transformation of parameters, to satisfy the translation property (Färe et al., 2005). This translation property ensures the distance from a plant's good and bad output bundle

[9] The i subscript on inputs and outputs have been omitted for simplicity.

to the technological frontier is minimized along the chosen direction vector. It reads

$$\vec{D}_i(x, y, b; g_y, -g_b) = \vec{D}_i(x, y + s \times g_y, b - s \times g_b; g_y, -g_b) + s \tag{2}$$

with s a scalar. The translation property excludes logarithmic specifications in turn, despite trans-log forms often being used in general output distance functions frameworks. Instead, we choose a quadratic distance function as in Färe et al. (2005) and Wei et al. (2013). With $k = 3$ inputs $x_{k,t}$ (capital, labor and energy), one desirable output y_t (sales revenue) and one pollutant b_t (CO_2 emissions), the directional distance function reads

$$\begin{aligned} D_{i,t}(x_{k,t}, y_t, b_t) = \alpha_0 + \sum_{k=1}^{3} \alpha_k x_{k,i,t} + \beta_1 y_{i,t} + \gamma_1 b_{i,t} + \frac{1}{2} \sum_{k=1}^{3} \sum_{k'=1}^{3} \alpha_{kk'} x_{k,i,t} x_{k',i,t} + \frac{1}{2} \beta_2 y_{i,t}^2 + \frac{1}{2} \gamma_2 b_{i,t}^2 \\ + \sum_{k=1}^{3} \delta_k x_{k,i,t} y_{i,t} + \sum_{k=1}^{3} \eta_n x_{k,i,t} b_{i,t} + \mu y_{i,t} b_{i,t} \end{aligned} \tag{3}$$

We choose the direction vector $g = (1, -1)$, which corresponds to a simultaneous expansion of production and contraction of pollution, as is standard in the related literature on shadow price estimation (Färe et al., 2006; Marklund & Samakovlis, 2007; Zhou et al., 2015; Wei et al., 2013).[10] Moreover, imposing the translation property to the quadratic specification requires the following parameter restrictions: (i) $\gamma_1 = \beta_1 + 1$, (ii) $\beta_2 = \gamma_2 = \mu_2$, (iii) $\delta_n = \eta_n$ and (iv) $\alpha_{nn'} = \alpha_{n'n}$.

The model then becomes

$$\begin{aligned} D_{i,t}(x_{i,k,t}, y_{i,t}, b_{i,t}) = \alpha_0 + \sum_{k=1}^{3} \alpha_k x_{k,i,t} + \beta_1 (y_{i,t} + b_{i,t}) + \frac{1}{2} \sum_{k=1}^{3} \sum_{k'=1}^{3} \alpha_{kk'} x_{k,i,t} x_{k',i,t} \\ + \frac{1}{2} \beta_2 (y_{i,t} + b_{i,t})^2 + \sum_{k=1}^{3} \delta_k x_{k,i,t} (y_{i,t} + b_{i,t}) + b_{i,t} \end{aligned} \tag{4}$$

which we calibrate below.

3.3 Frontier calibration

Next, we calibrate the parameters of equation 4, using a deterministic, linear programming method. Two reasons moved us away from an econometric estimation (or stochastic frontier analysis). First, it does not accommodate small sample sizes, yet we use data with a fine

[10] A sensitivity analysis of direction vectors can be found in Vardanyan & Noh (2006).

granularity to ensure comparability between production sites' activities. Besides, working at a dis-aggregated level enables us to analyze the effect of technological progress across sectors. Second, stochastic frontier analysis usually relies on maximum likelihood estimation (Murty et al., 2007; Behr, 2015; Löschel et al., 2019), which results are highly dependent on the assumptions about the distribution of errors. By contrast, the deterministic approach directly reveals the state of technology from the data, without other assumptions than the functional form of the technological frontier.

As in Färe et al. (2005) and Wei et al. (2013), we calibrate industries' technological frontiers using the following linear-quadratic program $\mathcal{P}$:

$$
\begin{aligned}
&Min \left[\vec{D}_{i,t}(x_{i,k,t}, y_{i,t}, b_{i,t}; g)\right] \quad \text{such that}\\
&\text{(a)} \quad \vec{D}_{i,t}(x_{i,k,t}, y_{i,t}, b_{i,t}; g) \geq 0\\
&\text{(b)} \quad \partial\vec{D}_{i,t}\Big/\partial y_{i,t} \leq 0\\
&\text{(c)} \quad \partial\vec{D}_{i,t}\Big/\partial b_{i,t} \geq 0\\
&\text{(d)} \quad \partial\vec{D}_{i,t}\Big/\partial x_{i,t} \geq 0\\
&\text{(e)} \quad \vec{D}_{i,t}(x_{i,k,t}, 0, 0; g) < 0
\end{aligned}
$$

Where $\vec{D}_{i,t}(x_{i,k,t}, y_{i,t}, b_{i,t}; g)$ is defined as in equation 4. Importantly, minimizing the distance removes any technical inefficiency, as plants are projected onto the technological frontier in the (b, y) space. In turn, $\hat{D}_{i,t}(x_{k,t}, y_t, b_t; g) = 0$ implicitly defines an expression for the technological frontier. Moreover, the program's constraints ensure that the production possibility set has the desired shape. In particular,

- (a) implies that observations are located on or under the technological frontier
- (b) and (c) imply that the distance to the frontier decreases (resp. increases) with respect to a marginal increase in the good (resp. bad) output
- (d) implies that inefficiency increases with input use
- (e) states that a positive amount of inputs must be associated with some production

Besides, $\mathcal{P}$ allows CO_2 emissions b to be positive with a null production, $y = 0$. This corresponds to residual emissions that can take place in practice, due to the preliminary heating of machinery for instance.

The linear-quadratic program $\mathcal{P}$ is run on industries' sequential production possibility sets, namely using observations from the initial date up to time t (Oh & Heshmati, 2010). For instance, 2014's frontier is obtained by calibrating the distance function on 2013 and 2014 observations, while 2015's frontier relies on 2013, 2014 and 2015 data (and so forth until 2017).[11] This approach enables us to take into account that a technologically feasible production set remains valid in the future. Thus, it implies that over time, technological progress can only push the technological frontier upwards. Moreover, and by contrast to a contemporaneous production set which only contains t-time observations, the sequential set embodies any technological change occurring from the initial date up until the year of interest. Last, we normalize input and output data by the samples' means[12] to avoid convergence problems (Färe et al., 2005; Wei et al., 2013).

4 Results

This section first presents results from the calibration of the distance function, namely technical efficiency and technological frontier estimates across industries and over time. Next, it analyzes the nature of technological progress in sample industries and last, discusses its effect on industry MAC curves.

4.1 Efficiency and technological change

Once technological frontiers calibrated, we start by computing plants' zero-cost abatement potential from the estimated distance to the technological frontier (or equivalently, technical efficiency score). Distance estimates corresponds to those emissions reductions that can be achieved by improving the technical efficiency of production without changing the quantity or allocation of inputs.

Denoting $\hat{D}_{i,t}(x_t, y_t, b_t)$ the calibrated distance function, the zero-cost abatement potential of plant i at time t corresponds to $\hat{D}_{i,t} \times \bar{b_t}$, with $\bar{b}_t$ the samples' mean pollution (recall that data is normalized). Table 3 reports average (over plants and years) values as a percentage of observed emissions. Results indicate that potential emission reductions due to technical efficiency improvements are important, ranging from 20 % in the chemical industry to more than 70 % in electricity and paper production. The dispersion of values within each sample

[11] In turn, year t sample has $(t - 2013 + 1) \times N$ observations.

[12] The average plant is defined by the $(x_{i,k,t}, y_{i,t}, b_{i,t}) = (1, 1, 1)$ coordinates

(standard deviations are reported in brackets) further indicates a strong heterogeneity in the data, with efficient plants operating on the technological frontier and others for which significant improvements are possible.

Furthermore, we analyze technological and efficiency changes across industries using a sequential Malmquist-Luenberger (SML) total factor productivity index. Developed by Chung et al. (1997), and adapted by Oh & Heshmati (2010) in the context of sequential production sets, the SML index enables to measure the evolution of plants' productivity over time. Specifically, the index can be decomposed into two terms capturing (i) changes in technical efficiency on the left (how far observations lie from the technological frontier), and (ii) technological progress (by how much the technological frontier expands). The plant-level, year-to-year index can be computed as

$$
\begin{aligned}
SML_i^{t,t+1} &= \left[\frac{D_i^t(x_t, y_t, b_t)}{D_i^t(x_{t+1}, y_{t+1}, b_{t+1})} \times \frac{D_i^{t+1}(x_t, y_t, b_t)}{D_i^{t+1}(x_{t+1}, y_{t+1}, b_{t+1})} \right]^{1/2} \\
&= \underbrace{\frac{D_i^t(x_t, y_t, b_t)}{D_i^{t+1}(x_{t+1}, y_{t+1}, b_{t+1})}}_{\text{Efficiency change (EC)}} \times \Bigg[\underbrace{\frac{D_i^{t+1}(x_t, y_t, b_t)}{D_i^t(x_t, y_t, b_t)} \times \frac{D_i^{t+1}(x_{t+1}, y_{t+1}, b_{t+1})}{D_i^t(x_{t+1}, y_{t+1}, b_{t+1})}}_{\text{Technological change (TC)}} \Bigg]^{1/2}
\end{aligned}
$$

To obtain the total productivity change over the period, the SML index can be chained over the years as follows

$$
\begin{aligned}
SML_i^{2013,2017} &= SML_i^{2013,2014} \times SML_i^{2014,2015} \times SML_i^{2015,2016} \times SML_i^{2016,2017} \\
&= (EC_i^{2013,2014} \times EC_i^{2014,2015} \times EC_i^{2015,2016} \times EC_i^{2016,2017}) \times \\
&\quad (TC_i^{2013,2014} \times TC_i^{2014,2015} \times TC_i^{2015,2016} \times TC_i^{2016,2017}) \\
&= EC_i^{2013,2017} \times TC_i^{2013,2017}
\end{aligned}
$$

Specifically, $SML_i^{2013,2017}$ indicates total factor productivity gains (resp. losses) over the period when > 1 (resp. < 1), and a constant productivity when $= 1$. Because of the sequential production set approach yet, the technological change component cannot be < 1 (Oh & Heshmati, 2010). In turn, any productivity loss is due to a decrease in technical efficiency. The plant average of $SML_i^{2013,2017}$, $EC_i^{2013,2017}$ and $TC_i^{2013,2017}$ are reported in Table 3.[13]

First, most industries experience total factor productivity gains over time. More precisely, these gains are more often due technological progress, rather than improvements in the

[13] We do not report intermediary, year-to-year indexes because no noticeable pattern stands out.

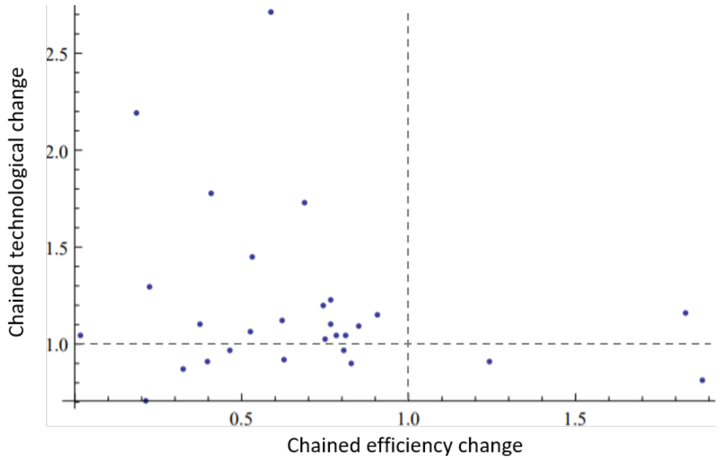
technical efficiency of production. However, the deterioration of technical efficiency observed in half of sample industries has to be nuanced. Let us indeed turn to Figure 4 which plots $EC_i^{2013,2017}$ against $TC_i^{2013,2017}$ for every observation in the metallurgy, low carbon-intensity sample. First, the majority of points lie in the upper left corner, which implies at first sight a negative correlation between technological progress and technical efficiency improvements ($TC_i^{2013,2017} > 1$ and $EC_i^{2013,2017} < 1$). Yet, Figure 4 shows that a few plants have carried out important technological progress over the period, which implies an important displacement of the technological frontier, and thereby increasing the distance to the majority of other firms.

Table 3: Efficiency and technical change

Industry	Carbon intensity	Zero-cost abatement potential (% of observed emissions)	Decomposition of the SML index		
			$SML^{2013,2017}$	$EC^{2013,2017}$	$TC^{2013,2017}$
Baked Clay (23.32)	0.4	35 % (0.17)	0.96 (0.85)	0.67 (0.31)	1.44 (0.92)
	3.6	55 % (0.30)	1.25 (1.66)	0.60 (0.71)	2.8 (2.01)
Cement (23.51)	5.1	20.3 % (0.13)	1.43 (2.52)	1.06 (1.37)	1.50 (1.32)
Chemicals (20.1)	0.3	56.2 % (0.27)	0.78 (0.49)	0.63 (0.38)	1.49 (1.28)
Electricity (35.11)	1.1	73.2 % (0.30)	1.05 (0.65)	1.12 (0.64)	1.11 (0.49)
Metallurgy (24.1)	0.1	24.2 % (0.11)	0.75 (0.43)	0.68 (0.42)	1.14 (0.50)
	0.5	28.5 % (0.15)	1.59 (4.01)	1.23 (2.62)	1.21 (0.47)
Paper (17.12)	0.1	71 % (0.17)	0.99 (0.83)	1.08 (1.56)	1.08 (0.20)
	0.5	41 % (0.22)	1.01 (0.75)	1.04 (0.30)	3.76 (2.63)
	1.1	39.5 % (0.31)	1.03 (0.72)	0.27 (0.28)	5.76 (4.89)
Plaster (23.52)	2.8	27.4 % (0.15)	0.94 (0.61)	0.98 (1.03)	1.22 (0.53)

Note: Zero-cost abatement potential represents the average technical efficiency improvement over years and production sites, reported in percentage of observed emissions. Standard deviations can be found in brackets. The full SML index and its two components are meaned over observations.

Figure 4: Distribution of SML index components, metallurgy (24.1)



Note: Low carbon-intensity sample. The reader may have noted that the chained technological change is sometimes lower than one, although we use a sequential production set approach. This is due to imperfections that come with the calibration of technological frontiers, and that are amplified by the multiplicative nature of the SML index.

Second, note that samples with a relatively low (resp. high) average carbon intensity tend to experience total factor productivity losses (resp. gains) over the period. Specifically, the technological change component ($TC^{2013,2017}$) increases with the carbon intensity of plants, like in baked clay products manufacturing, and the metallurgy and paper industries. This suggests that plants with a high carbon-intensity carry out more technical and/or technological efforts than low carbon-intensity ones, which has interesting policy implications discussed in Section 6. In particular, this result can be linked with the permit allocation method in the EU-ETS.

4.2 Nature of technological progress

Next, we analyze the nature of technological progress that took place at the industry level between 2013 and 2017, conforming to the theoretical framework outlined in Section 2. To do so, we compute a carbon intensity ratio as $CI^{LF}_{I,2017}/CI^{LF}_{I,2013}$, where $CI^{LF}_{I,t} = b^{LF}_{I,t}/y^{LF}_{I,t}$. More precisely, the value of the ratio indicates the evolution of $laisserfaire$ carbon intensity between the initial and last date. Therefore, a ratio < 1 indicates *directed* technological progress, while a ratio > 1 corresponds to *non-directed* technological progress. Coupled with information about the variation of baseline emissions, the carbon intensity ratio enables us to know whether *directed* technological progress is rather *weakly directed* or *strongly directed*.

Results are reported in Table 4. First, we learn that all types of technological progress took place over the period, depending on the industry considered. For instance, paper and baked clay manufacturers have consistently seen a decrease in $laisserfaire$ carbon intensity of production, by contrast to metallurgy, which has rather experienced *non-directed* technological progress. In four out of the eleven samples considered, plants did not carry out 'environmentally friendly' technological progress indeed, despite the environmental regulation. This puts into perspective the induced technological change literature, which typically focuses on low-carbon technologies.

Second, technological progress resulted in increasing most industries' baseline emissions, whether *directed* or *non-directed*. Specifically, technological progress can have a large influence on $laisserfaire$ emissions, with a percentage variation of more than 40 % between 2013 and 2017 in some sample industries (see cement and paper manufacturing for instance). Moreover, we find that technological progress tends to be *weakly directed* in industries where plants have a low carbon intensity on average, and *strongly directed* in higher carbon intensity industries. Interestingly, this suggests that high carbon-intensity plants translate the absolute limit on emissions in their technological strategy, resulting in a decrease in baseline emissions. However, low carbon-intensity plants rather carry out *weakly directed* technological progress, implying that they perceive the EU-ETS as a relative cap in practice. This argument will be developed in Section 6.

Table 4: Nature of technological progress

Industry	Carbon intensity	$CI^{LF}_{I,2017}/CI^{LF}_{I,2013}$	%Δ in baseline emissions	Nature of T.P.
Baked clay	0.4	0.96	+10.6 %	*weakly directed*
	3.6	0.52	-4.8 %	*strongly directed*
Cement	5.1	1.16	+45.9 %	*non-directed*
Chemicals	0.3	0.74	-8.5 %	*strongly directed*
Electricity	1.1	0.98	+6 %	*weakly directed*
Metallurgy	0.1	1.04	+15.7 %	*non-directed*
	0.5	1.03	+21.7 %	*non-directed*
Paper	0.1	0.93	+1.4 %	*weakly directed*
	0.5	0.61	-7.2 %	*strongly directed*
	1.1	0.49	-45.6 %	*strongly directed*
Plaster	2.8	1.03	+14.5 %	*non-directed*

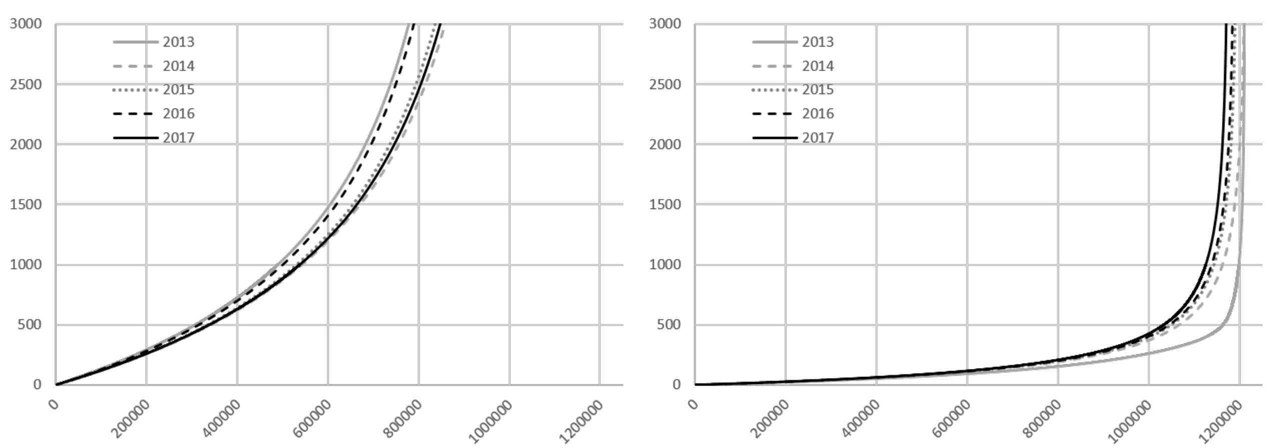
Note: %Δ corresponds to the percentage change between 2013 and 2017.

4.3 Effect of technological progress on MAC curves

Next, we compute industry marginal abatement cost curves, as outlined in section 2.2, and examine the effect of technological progress in the context of the EU-ETS. To do so, we keep inputs fixed at their 2013 (observed) level. This enables us to attribute year-to-year changes of MAC to displacements of the technological frontier only, thereby eliminating changes due to the quantity of inputs used. Figure 5 shows the resulting curves in baked clay product manufacturing. As expected, they are increasing and convex, contrasting with the usual linear specification used in theoretical models of carbon markets (Chaton et al., 2015, 2018; Chevallier, 2012; Salant, 2016; Perino & Willner, 2016; Pahle et al., 2018). Moreover, their asymptotes are equal to aggregate baselines net of residual emissions. Yet, residual emissions are negligible in baked clay, and never exceed 10 % of the baseline in general (see details in Table 8). Moreover, MAC are substantially higher in the low carbon intensity sample. Every unit of CO_2 abated leads to a greater revenue loss when carbon intensity is low indeed.

Figure 5: Marginal abatement cost curves, baked clay (23.32)

(a) Low carbon intensity (b) High carbon intensity



Note: The y-axis reports the marginal cost of abatement in €/tCO_2 and the x-axis reports abatement levels.

In order to characterize the dynamics of MAC curves under the influence of technological progress, we compute abatement efforts keeping the carbon price at an arbitrary level of 100€/tCO_2. Results, reported in table 5 reveals significant variations of abatement efforts depending on carbon intensity. In baked clay product manufacturing for instance, emissions reductions vary from 8 % to nearly 50 % between the two sub-samples. In the context of the EU-ETS, these results suggest large permit transfers from low to high carbon intensity industries. Yet, abatement efforts at the observed European Union Allowance (EUA) prices from 2013 to 2017 are of little magnitude, ranging from 0.1% to 5.8% in dirtier plants (Table 5). This can be due to the low price levels observed over the Phase 3 of the EU-ETS (6,5€/tCO_2 on average). Besides, our results suggest a large scope for emissions reductions in the EU-ETS: at a price of 25€/tCO_2, which corresponds to the price level observed in the last year, implied emissions reductions can reach 20 % in the most carbon-intensive industries (Table 8).

Furthermore, MAC dynamics are affected by the nature of technological progress. At a price of 100€/tCO_2, abatement can vary by more than 50 % between 2013 and 2017 due to technological change. Specifically, *non-directed* technological progress, as in the metallurgy or plaster industries, unambiguously increases the abatement effort for a given price of CO_2. This further means that MAC curves shift down over-time. By contrast, *strongly directed* technological progress results in decreasing the abatement effort between 2013 and 2017, in line with a decrease in baseline emissions (see baked clay, high carbon intensity in Table 5). Last, *weakly directed* technological progress yields greater abatement efforts for a given price, despite lowering the carbon intensity of production. Yet, note that technological progress resulted in increasing baseline emissions in most industries (i.e. was rarely *strongly directed*), thus amplifying the abatement effort at a given price.

Table 5: Summary of abatement dynamics

Industry	Carbon intensity	Nature of T.P.	Ave. abatement, EUA prices	Ave. abatement, 100€/tCO_2	%Δ in abatement, 100€/tCO_2
Baked clay	0.4	*weakly directed*	0.5 %	8.1 %	+10.4 %
	3.6	*strongly directed*	4.2 %	48.8 %	-10.9 %
Cement	5.1	*non-directed*	5.8 %	55.7 %	+57.1 %
Chemicals	0.3	*strongly directed*	1.1 %	13.4 %	-11.3 %
Electricity	1.1	*weakly directed*	1.3 %	19 %	+7.2 %
Metallurgy	0.1	*non-directed*	0.1 %	2.2 %	+16.7 %
	0.5	*non-directed*	0.6 %	10.2 %	+30.4 %
Paper	0.1	*weakly directed*	0.1 %	2.6 %	+3.9 %
	0.5	*strongly directed*	0.5 %	8.1 %	-13.3 %
	1.1	*strongly directed*	1.2 %	18.7 %	-28.4
Plaster	2.8	*non-directed*	3.2 %	39.4 %	+17 %

Note: %Δ corresponds to the percentage change between 2013 and 2017. The average abatement realized at EUA price is expressed in % of observed emissions, with $p_{2013}^{EUA} = 4$€/tCO_2, $p_{2014}^{EUA} = 5.1$€/tCO_2, $p_{2015}^{EUA} = 7.4$€/tCO_2, $p_{2016}^{EUA} = 6$€/tCO_2, $p_{2017}^{EUA} = 6.7$€/tCO_2.

Finally, we use computed industry MAC curves to analyze the price elasticity of pollution abatement at selected carbon price levels. Our results are consistent with that of Cialani

& Mortazavi (2018), in the context of industrial electricity demand. We first find that the elasticity of abatement demand is lower in high carbon-intensity industries. This may seem counter-intuitive, although it can be explained by the magnitude of MAC being lower for high carbon intensity plants, hence selected prices (10-500€/tCO_2) corresponding to the flatter part of the MAC curve. Second, and consistently with the convex shape of MAC curves, abatement becomes less elastic with higher price levels regardless of industries' carbon intensity. Last, we do not find that technological progress affects the price elasticity of abatement over time. This result confirms that MAC dynamics are mainly driven by variations in baseline emissions, rather than changes in the curvature of the technological frontier.

Table 6: Elasticity of emissions abatement

Industry	Carbon Intensity	Price elasticities				
		10€/tCO_2	25€/tCO_2	50€/tCO_2	100€/tCO_2	500€/tCO_2
Baked clay	0.4	0.99	0.98	0.96	0.93	0.72
	3.6	0.94	0.86	0.75	0.59	0.16
Cement	5.1	0.92	0.81	0.68	0.49	0.08
Chemicals	0.3	0.99	0.98	0.97	0.95	0.81
Electricity	1.1	0.98	0.95	0.91	0.84	0.47
Metallurgy	0.1	0.99	0.99	0.99	0.98	0.90
	0.5	0.99	0.97	0.95	0.92	0.68
Paper	0.1	0.99	0.99	0.98	0.97	0.89
	0.5	0.99	0.98	0.96	0.92	0.70
	1.1	0.98	0.95	0.91	0.84	0.48
Plaster	2.8	0.95	0.89	0.80	0.66	0.22

5 Equilibrium in the carbon market

In this section, we exploit permit allocation data from the EUTL and computed MAC curves to analyze the effect of technological progress on the carbon market equilibrium. This analysis should be taken as illustrative only, as our samples only account for a share of production sites covered under the EU-ETS (see Table 7).

Two ingredients are needed to simulate a market clearing price : an abatement demand, namely plants' baseline emissions and an abatement supply, namely plant's observed allocation. The equilibrium price is the one that equalizes supply and demand, as determined by the aggregate marginal abatement cost curves. Since plant's initial allocation is fixed by the regulatory authority, only marginal abatement cost curves and baseline emissions can be influenced by technological progress. Therefore, in order to isolate the effect of technological progress on equilibrium price levels, we set the permit supply (the exogenous allocation) at its 2013 level until 2017. However, we let the permit demand (endogenous baseline emissions and marginal abatement cost curves) vary over time, under the influence of technological progress. This enables us to compare how technological progress disturbs the market clearing price, in comparison to initial, i.e. 2013 conditions.

In our simulation exercise, we aggregate 2013's observed permit allocation and computed baseline emissions at the industry level. We do not consider the inter-temporal trading of permits (i.e. banking and borrowing) in order to isolate the direct effect of technological progress on market equilibrium.[14] Table 9 reports the observed level of permit allocation in 2013, emissions baseline and the resulting permit demand in the 11 samples. Note that the electricity sector does not receive any permits for free as a result of auctions being the default allocation method since 2013. Moreover, yearly variations in industries' abatement demand (2013's allocation minus annual baseline emission level) reflects the nature of technological progress that took place from 2013 to 2017. For instance, permit demand rose sharply in the cement and plaster industries, due to the increase in baseline emissions driven by *non-directed* technological progress (Table 9). By contrast, *strongly directed* technological progress led permit demand to decrease in the chemicals and paper industries.

In order to make 2013 computed price levels comparable with that observed on the EU-ETS, and since our samples only represent a share of regulated plants, we introduce an autonomous demand (it can be positive or negative). More precisely, the autonomous demand is calibrated to eliminate differences between the computed equilibrium price and observed EUA price in the initial year (2013), namely 4€/tCO_2. It is kept constant thereafter, so that price changes are only attributed to technological progress.

Besides, we compute permit supply as the total abatement realized for a given pollution price, namely the horizontal sum of industries' marginal abatement cost curves (Section 2.2). The market clearing price then equalizes permit demand, i.e. total baseline emissions plus the autonomous demand, to the market permit supply, which is driven by the permit price according to MAC curves. Next, we can find out the net permit demand at the industry level, at the computed clearing price. This enables us to analyze industries' net position in

[14] In an inter-temporal setting, inter-temporal arbitrages would indirectly affect market prices through the induced technological progress.

the market, namely the difference between permit demand (as baseline emissions minus free allocation) and realized abatement at the market clearing price. Table 7 reports the results.

First, and looking at net permit demands in equilibrium (Table 7), we find that all industries are permit buyers. This is due to the autonomous demand which is negative, thus adding up to the permit supply. It further means that the market equilibrium using our sample data alone would have resulted in a much higher clearing price than that observed in 2013 in the EU-ETS. This can be due to the large permit bank that was accumulated over the second trading period, and that we do not take into account here, or the small proportion of plants in notoriously over-allocated sectors such as chemicals and metallurgy (samples' share of emissions in the entire sector is reported in Table 7). Furthermore, it appears that higher carbon-intensity industries tend to hold a shorter position than low carbon ones. Intuitively, this implies that dirtier plants need to buy more allowances in the market than cleaner ones to cover their emissions. In turn, higher carbon-intensity plants bear the financial burden of permit purchases, which tends to be amplified by the price increase due to *non-directed* technological progress.

Second, and importantly, we find that technological progress has an overall upward effect equilibrium prices, under 2013's conditions. In 2013, the computed price is 4€/tCO_2 as a result of the autonomous being calibrated to reproduce the annual EUA price. Thereafter, the computed clearing price drops slightly below 2013's price level, but rises again and to the extent of 34€/tCO_2 from 2015 to 2017. Thus, if technological progress had occurred under 2013's conditions, it would have resulted in a much higher carbon price than observed. It implies that overall, technological progress tended to increase the aggregate permit demand through an increase of baseline emissions. This is due to its dominantly *weakly directed* or *non-directed* nature. Yet, our results suggest that *strongly directed* technological progress can be an instrument to alleviate compliance costs. In the paper industry for instance (high carbon intensity sample), technological progress can alleviate the net permit demand by more than 45%.

Yearly variations in the computed carbon price also seem to correlate with oil prices variations. Environmental technological progress is historically linked to oil prices indeed. In particular, Popp et al. (2020) show that high oil prices are associated with more green patents being filled. Between 2013 and 2014, Europe's brent spot price was peaking at the decade's maximum (above 100$/barrel).[15] This could have urged plants to save fuel costs and carry out *strongly directed* technological progress, relaxing the permit constraint on the EU-ETS

[15]Energy information administration : https://www.eia.gov/dnav/pet/hist/rbrteA.htm

and pushing down the market equilibrium price. On the contrary, oil prices declined by nearly 45% between 2014 and 2017, resulting in cheaper fuel and less economic benefits to cut emissions. This could explain the dominantly *non-directed* technological progress we observed, with an upward pressure on carbon prices.

Table 7: Market equilibrium

Industry	Emissions share	Carbon intensity	Net demand ($MtCO_2$)				
			2013	2014	2015	2016	2017
Baked Clay (23.32)	14.2 %	0.4	0.388	0.507	0.499	0.415	0.504
		3.6	0.676	0.698	0.619	0.437	0.438
Cement (23.51)	14.1 %	5.1	11.318	11.963	11.808	12.452	14.455
Chemicals (20.1)	4.8 %	0.3	6.779	5.532	5.708	5.657	5.675
Electricity (35.11)	1,2 %	1.1	32.733	34.057	33.707	32.304	32.345
Metallurgy (24.1)	3.1 %	0.1	1.934	1.944	2.284	2.461	2.507
		0.5	2.483	2.873	3.504	4.037	3.387
Paper (17.12)	13.9 %	0.1	0.389	0.570	0.553	0.535	0.395
		0.5	0.988	0.876	0.859	0.851	0.735
		0.9	5.221	3.468	2.910	4.198	2.833
Plaster (23.52)	12.4 %	2.8	3.301	3.772	3.887	2.963	3.045
Clearing price (€/tCO_2)			4	2.9	13	38.2	36.2
Price gap (€/tCO_2)			0	–1.1	+9	+34.2	+32.2

Note: The aggregate annual net demand sums up to minus calibrated autonomous demand, namely $-6.6214\times 10^7 tCO_2$. The price gap represents the difference between our simulated market clearing price and the average EUA price in 2013 (4€/tCO_2).

6 Policy Implications

In the context of the EU-ETS, we first find that *non-directed* technological change is at least as, if not more prevalent than *directed* technological progress for regulated, manufacturing plants. It implies that in presence of an environmental regulation, plants primarily seek total factor productivity gains, which can have repercussions on the outcomes of the policy. Furthermore, technological change often leads to increase baseline emissions, despite decreasing the carbon intensity of production. In our context of plants covered under the EU-ETS, this results in inflating the permit price, which affects the cost effectiveness of the regulation (section 5). The financial burden of regulated plants is indeed amplified through two channels: (i) a shorter market position and (ii) a dearer permit price. As a consequence, we find that only *strongly directed* technological progress enables to alleviate plants' compliance costs.

Interestingly, these results suggest that plants often perceive the EU-ETS as a relative cap on emissions in practice, namely a carbon intensity target, rather than an absolute limit on emissions, which it actually is. This is particularly salient when plants present a low average carbon intensity. We argue that this biased perception could be due to the allowance allocation method. In 2013, an allowance distribution method based on 'benchmarking' was implemented in the EU-ETS manufacturing sector. More precisely, free allocation is determined based on product benchmarks, defined as the average of the 10 % most greenhouse gas efficient installations in terms of carbon intensity of production over the years 2007-2008. Actual allocation levels are then computed by multiplying the benchmark by a historical production level and carbon leakage exposure factors. By setting a carbon-intensity standard within industries, 'dirtier' plants are incentivized to clean their production, while 'cleaner' ones receive all the permits needed to cover their emissions.[16]

For the time being, a single study assesses the impact of product benchmarks empirically (Sartor et al., 2014), and finds that the new allocation method reduces the scope for windfall gains by EU-ETS firms. Although this study does not conduct an impact evaluation of product benchmarks on technological adoption, our results suggest that they could contribute to homogenize plants' carbon intensity within industries. On the one hand, highly carbon intensive plants could have an incentive to carry out *strongly directed* technological progress and reduce their baseline emissions, in order to have a longer their position on the permit market. On the other hand, low carbon intensity plants, would rather benefit from the more generous permit endowment to carry out *weakly directed* or *non-directed* technological progress, and increase their total factor productivity.

We also believe that the directional distance function approach used in this study, which is also a benchmarking method, has several methodological advantages that make it an interesting alternative to the EU-ETS benchmarking procedure. First, the development of product benchmarks was rather costly and cumbersome, as it took two years of extensive consultations and expertise with various stakeholders. By contrast, the directional distance function analysis accommodates little input and output data at the plant level, making it possible to update technical efficiency scores and baseline emissions at little cost. The directional distance function method could prove helpful in updating historical emissions factors and benchmarks, as planned for the second half of Phase 4. This study also points

[16]Over the third (and current) trading period, a 43 % share of the total permit offer is covered by a product benchmark (European Commission)

out that relying on a grandfathering allocation method underrates the effect of technological progress on the effective abatement demand, with impacts on the carbon market outcomes.

Second, the directional distance function approach reflects plants' production process as a whole, including indirect emissions (related to energy or raw material purchase) to evaluate technical efficiency scores. By contrast, computing plants' permit allocation on the basis of their output, as is currently done in the EU-ETS, presents some shortcomings. Zipperer et al. (2017) raise that output-based allocation methods give an incentive to plants to outsource the production of upstream inputs to off-site facilities, in order to avoid indirect emissions being reflected in their emissions reports. By contrast, tuning plants' permit endowments on the basis of the efficiency input use, as is done in directional distance function approaches, could bring an incentive to optimize the production lines, with greater environmental impacts.

Acknowledgments

The authors would like to thank the anonymous referees of EconomiX and FAERE, as well as Stefan Ambec and Estelle Cantillon for their valuable comments and suggestions.

References

Acemoglu, D. (1998). Why do new technologies complement skills? Directed technical change and wage inequality. *The Quarterly Journal of Economics*, **113**, 1055–89.

Acemoglu, D. (2002). Directed technical change. *The Review of Economic Studies*, **69**, 781–809.

Acemoglu, D. (2007). Equilibrium bias of technology. *Econometrica*, **75**(5), 1371–1409.

Acemoglu, D., Aghion, P., Bursztyn, L. & Hemous, D. (2012). The environment and directed technical change. *American Economic Review*, **102**(1), 131–66.

Aghion, P., Dechezleprêtre, A., Hemous, D., Martin, R. & Van Reenen, J. (2016). Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry. *Journal of Political Economy*, **124**(1), 1–51.

Alberola, E., Chevallier, J. & Chèze, B. (2008). Price drivers and structural breaks in european carbon prices 2005–2007. *Energy Policy*, **36**(2), 787–797.

Baudry, M., Faure, A. & Quemin, S. (2021). Emissions trading with transaction costs. *Journal of Environmental Economics and Management*, **108**, 102468.

Beck, U. & Kruse-Andersen, P. (2018). Endogenizing the cap in a cap-and-trade system: Assessing the agreement on EU-ETS phase 4. *De Økonomiske Råd*.

Behr, A. (2015). *Production and efficiency analysis with R*. Springer.

Borghesi, S., Crespi, F., D'Amato, A., Mazzanti, M. & Silvestri, F. (2015). Carbon abatement, sector heterogeneity and policy responses: evidence on induced eco innovations in the EU. *Environmental Science & Policy*, **54**, 377–388.

Calel, R. (2020). Adopt or innovate: Understanding technological responses to cap-and-trade. *American Economic Journal: Economic Policy*, **12**(3), 170–201.

Calel, R. & Dechezleprêtre, A. (2016). Environmental policy and directed technological change: evidence from the european carbon market. *Review of Economics and Statistics*, **98**(1), 173–191.

Chambers, R. G., Chung, Y. & Färe, R. (1998). Profit, directional distance functions, and nerlovian efficiency. *Journal of Optimization Theory and Applications*, **98**(2), 351–364.

Chaton, C., Creti, A. & Peluchon, B. (2015). Banking and back-loading emission permits. *Energy Policy*, **82**, 332–341.

Chaton, C., Creti, A. & Sanin, M.-E. (2018). Assessing the implementation of the market stability reserve. *Energy Policy*, **118**, 642–654.

Chevallier, J. (2012). Banking and borrowing in the eu-ets: A review of economic modelling, current provisions and prospects for future design. *Journal of Economic Surveys*, **26**(1), 157–176.

Chung, Y. H., Färe, R. & Grosskopf, S. (1997). Productivity and undesirable outputs: a directional distance function approach. *Journal of Environmental Management*, **51**(3), 229–240.

Cialani, C. & Mortazavi, R. (2018). Household and industrial electricity demand in Europe. *Energy Policy*, **122**, 592–600.

Coelli, T. J., Rao, D. S. P., O'Donnell, C. J. & Battese, G. E. (2005). *An introduction to efficiency and productivity analysis*. Springer Science & Business Media.

Creti, A., Jouvet, P.-A. & Mignon, V. (2012). Carbon price drivers: Phase I versus phase II equilibrium? *Energy Economics*, **34**(1), 327–334.

De Perthuis, C. & Trotignon, R. (2014). Governance of CO2 markets: Lessons from the EU-ETS. *Energy Policy*, **75**, 100–106.

Ellerman, A. D., Valero, V. & Zaklan, A. (2015). *An analysis of allowance banking in the EU-ETS*. Working Paper RSCAS 2015/29, European University Institute.

Färe, R., Grosskopf, S., Noh, D.-W. & Weber, W. (2005). Characteristics of a polluting technology: theory and practice. *Journal of Econometrics*, **126**(2), 469–492.

Färe, R., Grosskopf, S. & Weber, W. L. (2006). Shadow prices and pollution costs in US agriculture. *Ecological Economics*, **56**(1), 89–103.

Friedrich, M., Mauer, E.-M., Pahle, M. & Tietjen, O. (2020). From fundamentals to financial assets: the evolution of understanding price formation in the EU-ETS.

Gerlagh, R., Kverndokk, S. & Rosendahl, K. E. (2009). Optimal timing of climate change policy: Interaction between carbon taxes and innovation externalities. *Environmental and Resource Economics*, **43**(3), 369–390.

Goulder, L. H. & Mathai, K. (2000). Optimal CO2 abatement in the presence of induced technological change. *Journal of Environmental Economics and Management*, **39**(1), 1–38.

Goulder, L. H. & Schneider, S. H. (1999). Induced technological change and the attractiveness of CO2 abatement policies. *Resource and Energy economics*, **21**(3-4), 211–253.

Grubb, M., Duong, M. & Chapuis, T. (1994). Optimizing climate change abatement responses: on inertia and induced technology development. *Integrative Assessment of Mitigation, Impacts, and Adaptation to Climate Change*, (09), 513–534.

Hicks, J. (1932). *The theory of wages*. Springer.

Hintermann, B. (2010). Allowance price drivers in the first phase of the EU-ETS. *Journal of Environmental Economics and Management*, **59**(1), 43–56.

Hintermann, B., Peterson, S. & Rickels, W. (2016). Price and market behavior in phase II of the EU-ETS: A review of the literature. *Review of Environmental Economics and Policy*, **10**(1), 108–128.

Hitzemann, S., Uhrig-Homburg, M. & Ehrhart, K.-M. (2015). Emission permits and the announcement of realized emissions: Price impact, trading volume, and volatilities. *Energy Economics*, **51**, 560–569.

Kaya, Y. (1989). Impact of carbon dioxide emission control on gnp growth: interpretation of proposed scenarios. *Intergovernmental Panel on Climate Change/Response Strategies Working Group, May*.

Koch, N., Fuss, S., Grosjean, G. & Edenhofer, O. (2014). Causes of the EU-ETS price drop: recession, CDM, renewable policies or a bit of everything? New evidence. *Energy Policy*, **73**, 676–85.

Koch, N., Grosjean, G., Fuss, S. & Edenhofer, O. (2016). Politics matters: regulatory events as catalysts for price formation under cap-and-trade. *Journal of Environmental Economics & Management*, **78**, 121–39.

Landis, F. (2015). *Final report on marginal abatement cost curves for the evaluation of the market stability reserve*. Technical report, ZEW-Dokumentation.

Löschel, A., Lutz, B. J. & Managi, S. (2019). The impacts of the eu-ets on efficiency and economic performance–an empirical analyses for german manufacturing firms. *Resource and Energy Economics*, **56**, 71–95.

Marklund, P. & Samakovlis, E. (2007). What is driving the eu burden-sharing agreement: efficiency or equity? *Journal of Environmental Management*, **85**(2), 317–29.

McKinsey, C. (2009). Pathways to a low carbon economy – version 2 of the global greenhouse gas abatement cost curve, McKinsey&Company.

Murty, M. N., Kumar, S. & Dhavala, K. K. (2007). Measuring environmental efficiency of industry: a case study of thermal power generation in india. *Environmental and Resource Economics*, **38**(1), 31–50.

Oh, D.-h. & Heshmati, A. (2010). A sequential malmquist–luenberger productivity index: environmentally sensitive productivity growth considering the progressive nature of technology. *Energy Economics*, **32**(6), 1345–1355.

Pahle, M., Burtraw, D., Tietjen, O., Flachsland, C. & Edenhofer, O. (2018). Preserving the integrity of the EU-ETS under unilateral action. In *World Congress for Environmental and Resource Economics, Gothenburg*.

Perino, G. & Willner, M. (2016). Procrastinating Reform: The Impact of the Market Stability Reserve on the EU-ETS. *Journal of Environmental Economics & Management*, **80**, 37–52.

Popp, D., Pless, J., Haščič, I. & Johnstone, N. (2020). *Innovation and Entrepreneurship in the Energy Sector*. Technical report, National Bureau of Economic Research.

Porter, M. E. & Van der Linde, C. (1995). Toward a new conception of the environment-competitiveness relationship. *Journal of Economic Perspectives*, **9**(4), 97–118.

Quemin, S. & Trotignon, R. (2019). *Emissions Trading with Rolling Horizons*. Working Paper, Grantham Research Institute, LSE.

Quemin, S. & Trotignon, R. (2021). Emissions trading with rolling horizons. *Journal of Economic Dynamics and Control*, **125**, 104099.

Rickels, W., Görlich, D. & Peterson, S. (2015). Explaining european emission allowance price dynamics: Evidence from phase ii. *German Economic Review*, **16**(2), 181–202.

Salant, S. W. (2016). What ails the european union's emissions trading system? *Journal of Environmental Economics and Management*, **80**, 6–19.

Sartor, O., Pallière, C. & Lecourt, S. (2014). Benchmark-based allocations in EU-ETS phase 3 : an early assessment. *Climate Policy*, **14**(4), 507–524.

Shephard, R. (1970). *Theory of cost and production functions*. Princeton University Press.

Tietenberg, T. H. & Lewis, L. (2016). *Environmental and natural resource economics*. Routledge.

Tietjen, O., Lessmann, K. & Pahle, M. (2020). Hedging and temporal permit issuances in cap-and-trade programs: The market stability reserve under risk aversion. *Available at SSRN 3436736*.

Van Leeuwen, G. & Mohnen, P. (2017). Revisiting the porter hypothesis: an empirical analysis of green innovation for the netherlands. *Economics of Innovation and New Technology*, **26**(1-2), 63–77.

Vardanyan, M. & Noh, D.-W. (2006). Approximating pollution abatement costs via alternative specifications of a multi-output production technology: a case of the US electric utility industry. *Journal of Environmental Management*, **80**(2), 177–90.

Wei, C., Löschel, A. & Liu, B. (2013). An empirical analysis of the co2 shadow price in chinese thermal power enterprises. *Energy Economics*, **40**, 22–31.

Zhou, P., Zhou, X. & Fan, L. (2014). On estimating shadow prices of undesirable outputs with efficiency models: A literature review. *Applied Energy*, **130**, 799–806.

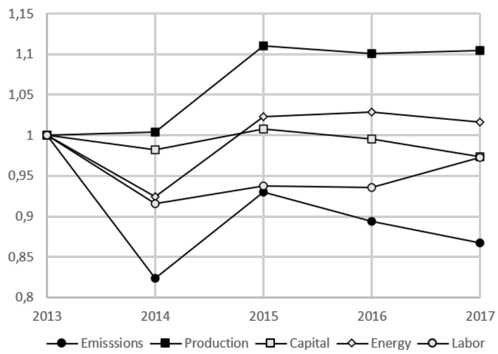
Zhou, X., Fan, L. & Zhou, P. (2015). Marginal CO2 abatement costs: Findings from alternative shadow price estimates for shanghai industrial sectors. *Energy Policy*, **77**, 109–117.

Zipperer, V., Sato, M. & Neuhoff, K. (2017). *Benchmarks for emissions trading–general principles for emissions scope*. Discussion paper, DIW Berlin.

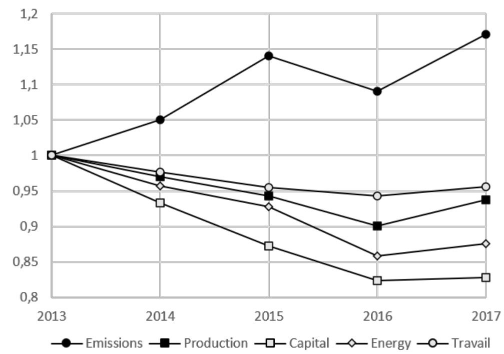
Appendix

Figure 6: Input and output dynamics across industries

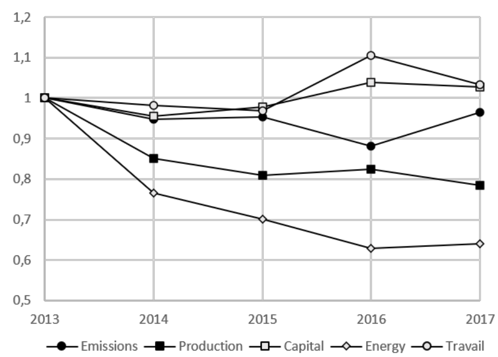
(a) Baked Clay - High carbon intensity



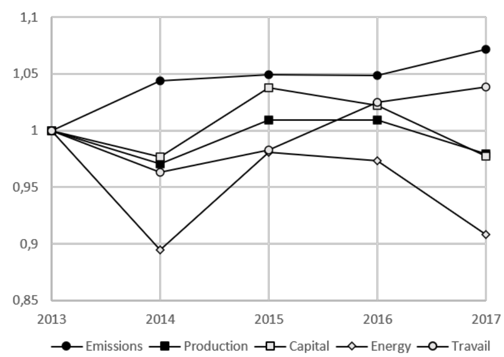
(b) Baked clay - Low carbon intensity



(c) Chemicals



(d) Cement



(e) Electricity

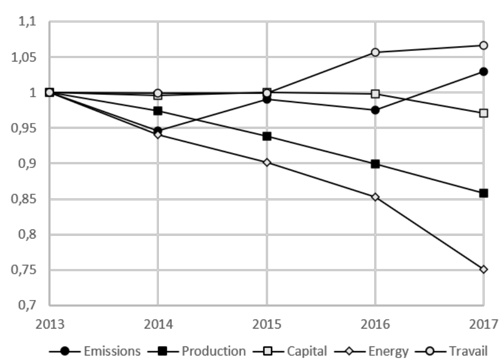
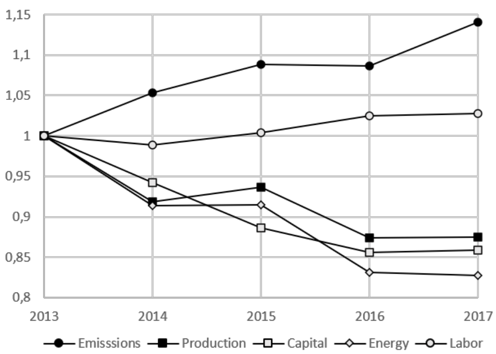
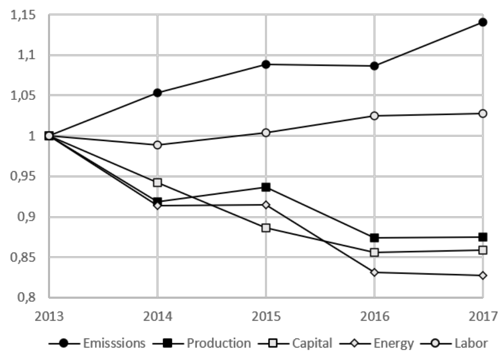


Figure 7: Input and output dynamics across industries - continued

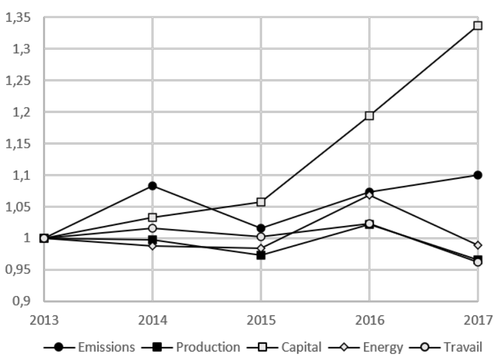
(a) Metallurgy - High carbon intensity



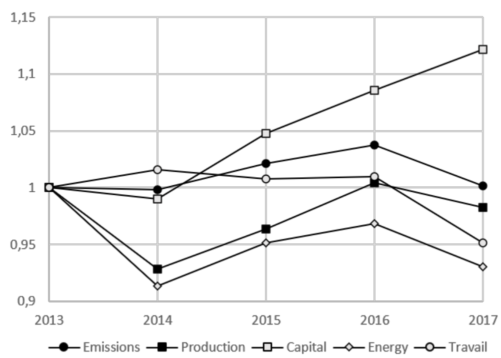
(b) Metallurgy - Low carbon intensity



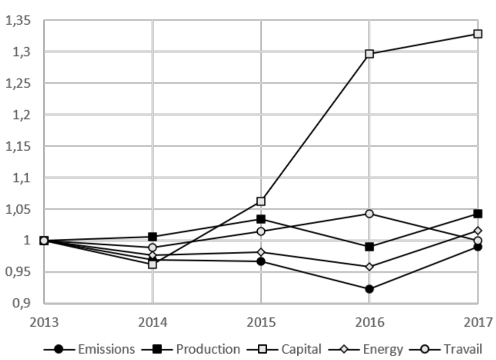
(c) Paper - Low carbon intensity



(d) Paper - Medium carbon intensity



(e) Paper - High carbon intensity



(f) Plaster

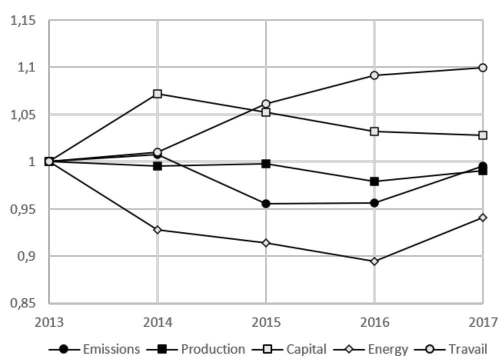


Table 8: Abatement dynamics: details

Industry	Carbon Intensity	Year	Baseline emissions ($mtCO_2$)	Residual emissions	Abatement EUA price	Abatement 25€/tCO_2	Abatement 100€/tCO_2	Δabatement$_{t-1,t}$, 100€/tCO_2
Baked clay	0.4	2013	0.963	1.7 %	0.3 %	2.1 %	8 %	0 %
		2014	1.045	1.9 %	0.4 %	2.1 %	8.1 %	+10.8 %
		2015	1.099	1.5 %	0.6 %	2.2 %	8.2 %	-2.1 %
		2016	0.958	1.4 %	0.5 %	2.1 %	8.2 %	-5.8 %
		2017	1.036	1.5 %	0.6 %	2.1 %	8.2 %	7.5 %
	3.6	2013	1.233	1.6 %	3.1 %	17.7 %	51.1 %	0 %
		2014	1.216	0 %	3.7 %	16.1 %	46.6 %	-10 %
		2015	1.196	0 %	5.2 %	16.2 %	46.6 %	-1.6 %
		2016	1.190	0 %	4.3 %	16.2 %	46.7 %	-0.4 %
		2017	1.176	0 %	4.8 %	16.2 %	46.7 %	+1.1 %
Cement	5.1	2013	30.820	10.3 %	3.8 %	20.5 %	53.8 %	0 %
		2014	31.153	9.5 %	4.9 %	20.4 %	53.4 %	+0.4 %
		2015	34.211	7.6 %	7.1 %	21.1 %	55.2 %	+13.5 %
		2016	44.677	4.8 %	6.1 %	22.2 %	58.2 %	+37.4 %
		2017	44.988	4.1 %	6.9 %	22.3 %	58.6 %	+5.8 %
Chemicals	0.3	2013	10.920	0.05 %	0.6 %	3.6 %	11.3 %	0 %
		2014	9.663	0.8 %	0.8 %	3.8 %	11.8 %	-15.8 %
		2015	9.894	0.1 %	1.3 %	4.1 %	12.6 %	+3.2 %
		2016	9.980	0.02 %	1.4 %	5.2 %	15.3 %	+1.2 %
		2017	9.987	0.03 %	1.6 %	5.4 %	15.8 %	+0.1 %
Electricity	1.1	2013	33.022	0.8 %	0.9 %	5.3 %	18.7 %	0 %
		2014	34.276	0.4 %	1.1 %	5.3 %	18.9 %	+4.4 %
		2015	34.883	0.1 %	1.6 %	5.3 %	19 %	+1.8 %
		2016	35.108	0.05 %	1.3 %	5.3 %	19 %	+1.3 %
		2017	35.009	0.1 %	1.5 %	5.3 %	19 %	-0.3 %

Industry	Carbon Intensity	Year	Baseline emissions ($mtCO_2$)	Residual emissions	Abatement EUA price	Abatement 25€/tCO_2	Abatement 100€/tCO_2	Δabatement$_{t-1,t}$, 100€/tCO_2
Metallurgy	0.1	2013	3.873	8.1 %	0.1 %	0.6 %	2.2 %	0 %
		2014	3.888	8.4 %	0.1 %	0.5 %	2.2 %	-0.4 %
		2015	4.232	8.6 %	0.2 %	0.5 %	2.2 %	+9.3 %
		2016	4.436	6.9 %	0.1 %	0.6 %	2.2 %	+6.9 %
		2017	4.481	6.9 %	0.1 %	0.6 %	2.2 %	+0.95 %
	0.5	2013	5.208	11.8 %	0.4 %	2.5 %	9.5 %	0 %
		2014	5.594	9.9 %	0.5 %	2.6 %	9.7 %	+9.8 %
		2015	6.299	4.7 %	0.8 %	2.7 %	10.3 %	+19.7 %
		2016	7.037	3.6 %	0.6 %	2.8 %	10.5 %	+13.4 %
		2017	6.338	6.6 %	0.7 %	2.7 %	10.2 %	-12.5 %
Paper	0.1	2013	1.274	1.7 %	0.1 %	0.6 %	2.6 %	0 %
		2014	1.456	1 %	0.1 %	0.7 %	2.6 %	+15.1 %
		2015	1.442	1 %	0.2 %	0.7 %	2.6 %	-1 %
		2016	1.433	1.1 %	0.1 %	0.7 %	2.6 %	-0.6 %
		2017	1.292	0.8 %	0.2 %	0.7 %	2.6 %	-9.6 %
	0.5	2013	2.637	9.3 %	0.4 %	2.2 %	8.5 %	0 %
		2014	2.522	10.1 %	0.4 %	2.1 %	8 %	-10.6 %
		2015	2.526	9.9 %	0.6 %	2.1 %	8 %	+0.4 %
		2016	2.574	8.2 %	0.5 %	2.1 %	8.2 %	+3.8 %
		2017	2.448	10.2 %	0.6 %	2.1 %	8 %	-6.9 %
	1.1	2013	6.745	1.4 %	0.9 %	5.6 %	20.1 %	0 %
		2014	4.960	6.2 %	1.1 %	5.2 %	18.4 %	-32.5 %
		2015	4.491	4.2 %	1.5 %	5 %	18 %	-11.5 %
		2016	6.141	0 %	1.3 %	5.2 %	18.7 %	+42.2 %
		2017	4.631	2.7 %	1.4 %	5.1 %	18.2 %	-26.6 %
Plaster	2.9	2013	6.984	6.5 %	2.2 %	12.7 %	39.2 %	0 %
		2014	7.419	6 %	2.8 %	12.6 %	38.7 %	+6.7 %
		2015	7.972	4.1 %	4.1 %	12.8 %	39.4 %	+9.7 %
		2016	7.974	4 %	3.3 %	12.8 %	39.4 %	+0.1 %
		2017	7.997	3.8 %	3.7 %	12.8 %	39.4 %	+0.5 %

Note: Residual emissions are reported as a percentage of the total baseline. The Malmquist index measures the percentage increase in the technological frontier relative to the previous year, at $b = x\%$ of baseline emissions. Average annual EUA prices are: $p^{EUA}_{2013} = 4$€/tCO_2, $p^{EUA}_{2014} = 5.1$€/tCO_2, $p^{EUA}_{2015} = 7.4$€/tCO_2, $p^{EUA}_{2016} = 6$€/tCO_2, $p^{EUA}_{2017} = 6.7$€/tCO_2 . Abatement is expressed as a percentage of annual observed emissions.

Table 9: Abatement demand ($mtCO_2$) - details

	Industry	Baked Clay		Cement	Chemicals	Electricity	Metallurgy		Paper			Plaster
		0.4	3.6				0.1	0.5	0.1	0.5	0.9	
2013	Baseline	0.963	1.233	30.820	10.920	33.021	3.873	5.208	1.274	2.637	6.745	6.984
	Allocation	0.571	0.518	18.328	4.116	0	1.936	2.704	0.884	1.639	1.460	3.528
	Demand	0.391	0.715	12.492	6.804	33.021	1.1937	2.504	0.390	0.998	5.284	3.456
2014	Baseline	1.045	1.216	31.153	9.663	34.276	3.883	5.594	1.456	2.522	4.960	7.419
	Allocation	0.571	0.518	18.328	4.116	0	1.936	2.704	0.884	1.639	1.460	3.528
	Demand	0.473	0.698	12.824	5.546	34.276	1.947	2.891	0.571	0.883	3.499	3.890
2015	Baseline	1.009	1.196	34.211	9.894	34.688	4.232	6.299	1.442	2.526	4.491	7.972
	Allocation	0.571	0.518	18.328	4.116	0	1.936	2.704	0.884	1.639	1.460	3.528
	Demand	0.438	0.678	15.882	5.778	34.688	2.296	3.595	0.558	0.887	3.030	4.444
2016	Baseline	0.958	1.190	44.677	9.980	35.107	4.436	7.037	1.433	2.574	6.141	7.974
	Allocation	0.571	0.518	18.328	4.116	0	1.936	2.704	0.884	1.639	1.460	3.528
	Demand	0.386	0.672	26.349	5.863	35.107	2.500	4.333	0.549	0.935	4.680	4.446
2017	Baseline	1.035	1.177	46.930	9.987	35.008	4.481	6.338	1.292	2.448	4.631	7.997
	Allocation	0.571	0.518	18.328	4.116	0	1.936	2.704	0.884	1.639	1.460	3.528
	Demand	0.464	0.659	28.602	5.871	35.008	2.544	3.634	0.408	0.809	3.170	4.469

WORKING PAPER

PREVIOUS ISSUES

Working Paper Publication Director : Philippe Delacote

The views expressed in these documents by named authors are solely the responsibility of those authors. They assume full responsibility for any errors or omissions.

The Climate Economics Chair is a joint initiative by Paris-Dauphine University, CDC, TOTAL and EDF, under the aegis of the European Institute of Finance.