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Carbon abatement in the European chemical industry: assessing the feasibility of abatement technologies by estimating firm-level marginal abatement costs

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ABSTRACT

As many other industries, the chemical industry has to strongly reduce its' carbon emissions, for which various abatement technologies exist. We study the economic feasibility of these abatement technologies by estimating the Marginal Abatement Cost (MAC) of CO_2 emissions for 24 firms in the European chemical sector over the period 2015–2020. We estimate the firm-level MAC by using a quadratic directional output distance function (DDF) model. We find a median MAC of 429 €/t CO_2, which is significantly above current carbon prices, indicating that most firms in this industry prefer to use carbon allowances instead of reducing their own emissions. We conclude that carbon abatement in the chemical industry is only likely when the carbon price is significantly higher or when financial support is provided for certain abatement technologies, such as renewable hydrogen and bio-based ammonia.

1. Introduction

The European chemical industry is one of the most energy-intensive industries in the European economy and the largest industrial energy consumer in the EU-28, accounting for approximately 21% of final energy consumption (50.8 million tons of oil equivalent) in the EU-28 industry sector in 2019 (Eurostat, 2022).[1] As the sector's current energy input is mostly based on fossil fuels, predominantly oil and gas, the chemical sector is a relatively large contributor to European greenhouse gas (GHG) emissions.[2] According to the European Environment Agency (EEA, 2021), the EU-28 chemical industry emitted a total of 132 million tons (Mt) of GHG emissions relating to the on-site combustion of fuels to generate energy and the direct emissions from production processes in 2019, about 3.5% of total net GHG emissions in the EU-28 in the same year. To reach the economy-wide targets as stated in the European Green Deal (EC, 2019), which include a 55% net carbon emission reduction by 2030 and carbon neutrality by 2050, the chemical sector needs to take measures to reduce the energy and carbon intensity of production.

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[1] The industry sector can be classified into manufacturing, non-manufacturing and energy-sectors, including iron and steel, chemical and petrochemical, non-ferrous metals, non-metallic minerals, transport equipment, machinery equipment, mining and quarrying, food, beverages and tobacco, paper, pulp and printing, wood and wood products, construction, textile and leather.

[2] We use the term greenhouse gas (GHG) emissions, carbon dioxide equivalent (CO_2e) emissions, and (carbon) emissions interchangeably to cover all the emissions included in the Kyoto Protocol: carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), sulfur hexafluoride (SF_6), and nitrogen trifluoride (NF_3). CO_2-equivalent is a single metric that allows for comparing the emissions from these various GHGs based on their global warming potential.

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There are various options to decarbonize, including demand-side measures, energy efficiency improvements (e.g., retrofitting existing plants and buildings to reduce energy consumption), using biomass or hydrogen for energetic (heating) and non-energetic (feedstock) purposes, electrifying heat provision (e.g., using low-carbon electricity in electric boilers to replace gas-fired boilers), and carbon capture and storage (CCS). However, besides considering technical feasibility, firms have to consider the economic feasibility of the available carbon abatement measures to allocate their investments efficiently. From a welfare perspective, an efficient allocation of investment capital associated with carbon abatement is important to minimize the total abatement costs of reaching climate targets. It is desirable that market players exercise least cost abatement measures first.

The decision of market players to invest in abatement technologies is based on the opportunity costs of replacing existing for alternative technologies. The opportunity costs are determined by the marginal abatement cost (MAC) of a given abatement measure, which is the cost (in €/t CO_2e) associated with the last unit of emission abatement for a given quantity of emission reduction. Therefore, estimates of the MAC can provide valuable information on the economics of carbon emission abatement and the economic potential of carbon abatement measures in the European chemical sector. In addition, MAC estimates may contribute to the cost-efficient design and implementation of carbon reduction policies specifically targeted at the chemical industry, including policies providing subsidies or tax-benefits for certain low-carbon technologies.

This study estimates and maps the distribution of the MAC in the chemical industry by evaluating firms' carbon intensity levels relative to those of efficient peers with comparable production activities. We estimate the firm-level MAC using the distance function approach under the production theory framework, which models the firm as a producer of both desirable and undesirable outputs given a set of economic and technical constraints. This theoretical framework states that the MAC (or shadow price) measures the trade-off between desirable and undesirable outputs (e.g., carbon emissions) or, stated differently, the value of the desirable output foregone to abate the undesirable output by one unit.

More specifically, we estimate firm-level MAC using the directional output distance function (DDF) method (Chung et al., 1997; Färe et al., 2005). The DDF is defined as the translation of a point (defined by a particular desirable and undesirable output combination) towards the efficient frontier along a specified vector, i.e. the directional vector (Jain and Kumar, 2018). The DDF allows for both proportional and non-proportional changes in outputs in order to reach the efficient frontier, expanding the desirable output and contracting the undesirable output in any chosen direction (Chambers et al., 1998; Färe et al., 2005). Further, the DDF measures firms' technical and environmental efficiency, which is given by the deviation of each firm from the boundary of the output set. This efficiency provides information on about the extent to which firms, if they were to operate efficiently, are able to expand their desirable outputs and reduce their undesirable outputs. Previous literature has applied the DDF to estimate the MAC at the regional level, industrial level, for electric utilities at plant- or firm-level, and for firms in the iron and steel industry (Matsushita and Yamane, 2012; Peng et al., 2012; Wei et al., 2013; Du et al., 2015; Xiao et al., 2017; Ma and Hailu, 2016; Wang et al., 2017; Jain and Kumar, 2018; Ji and Zhou, 2020).

This study contributes to the literature in several ways. First, we provide an assessment of the firm-level MAC within the European chemical industry. Second, we compare the estimated MACs to the prevailing carbon market prices in the EU Emission Trading System (EU-ETS) to determine the extent to which firms are incentivized to engage in actual abatement activities. Third, we compare the estimated MACs with data on the cost of various abatement technologies available in the chemical sector to identify the feasible options for emission reduction in various parts of the industry.

Our dataset consists of 24 firms active in the European chemical industry over the period 2015 to 2020.[3] We measure the level of firm efficiency by crediting firms for reducing their average carbon emission intensity per unit of output, rather than for reducing their absolute emissions. More specifically, we assume that firms' production and carbon abatement strategies are based on a good output-maximizing approach, which corresponds to the practice of relative benchmarking for industries in the EU-ETS. We specify the DDF parametrically using the quadratic functional form and estimate shadow prices using the linear programming method by Aigner and Chu (1968). In the second step, we compare our derived MACs to the carbon market price and the cost of various abatement technologies available in the chemical sector.

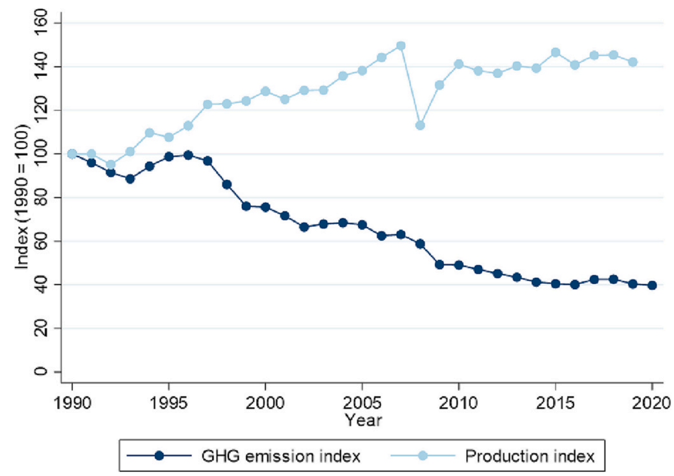

Fig. 1. GHG emissions index for the chemical industry (CRF2B) and fuel combustion in the production of chemicals (CRF1A2C) in the EU-28 in the period 1990–2020 and production index for the manufacture of chemicals and chemical products (C20) in the EU-28 in the period 1990–2019. Source: European Environment Agency (2021), Eurostat (2022), Cefic (2022).

This study finds that the estimated median shadow price of CO_2-emissions for the assumed abatement strategy of firms in the European chemical sector is 429 €/t CO_2. Further, we find that the representative firm can reduce its' carbon intensity with 3.96% if it were to operate efficiently, which can be achieved by increasing revenues by €333.78 million while holding carbon emissions constant. In addition, we find a significant variation in firm-level MACs, which suggests that firms have different technological options to lower their carbon emissions. Notably, the range of abatement costs for the available carbon reduction technologies in the chemical industry is comparable to the range of our estimated firm-level MACs. Moreover, the median MAC indicates that the current market carbon price in the EU-ETS is not sufficient to induce the representative firm to engage in abating activities within the firm. At last, the regression analysis of the determining factors of the estimated shadow prices finds that the shadow prices are negatively associated with carbon intensity, energy intensity and market capitalization, indicating increasing returns to scale in carbon emission abatement.

The remaining sections are structured as follows. Section 2 describes the development of GHG emissions in the EU-28 chemical sector and the available technologies for carbon abatement. Section 3 provides the literature review on estimating the MAC. Section 4 provides the theoretical and empirical specification of our model. Section 5 describes the

[3] The firms in our sample had an aggregated revenue (net sales) of 204 billion in 2018, which is about 36% of the 565 billion in sales of the total EU-28 chemicals industry in 2018 (Cefic, 2022). Additionally, these firms collectively generated about 86 million ton of CO_2-equivalent emissions, which represents approximately 64% of the total emissions of 139 million ton in the EU-28 chemical industry in 2018 (EEA, 2021; Bloomberg, 2022). Hence, our sample represents a significant part of the European chemical industry.

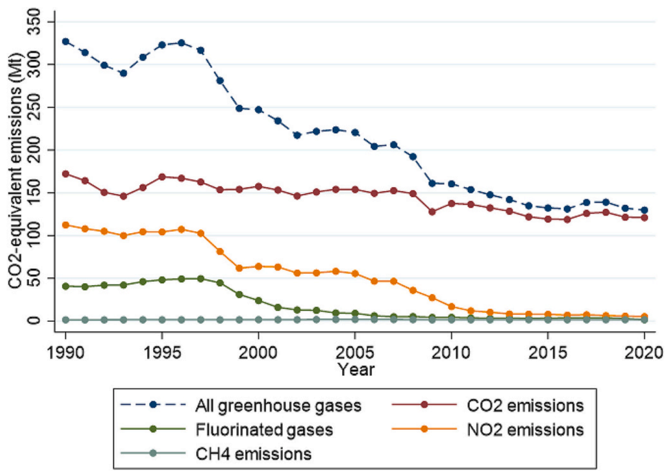

Fig. 2. CO_2-equivalent emissions per type of GHG from the chemical industry (CRF2B) and fuel combustion in the production of chemicals (CRF1A2C) in the EU-28 in the period 1990–2020. Source: European Environment Agency (2021), Cefic (2022).

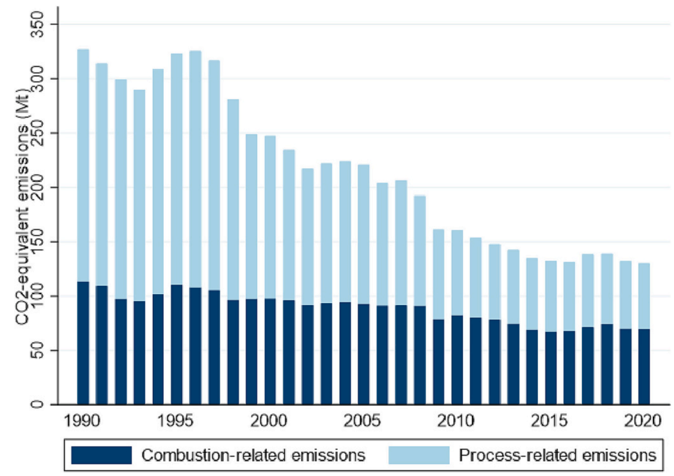

Fig. 3. Combustion emissions and process emissions from the chemical industry (CRF2B) and fuel combustion in the production of chemicals (CRF1A2C) in the EU-28 in the period 1990–2020. Source: European Environment Agency (2021), Cefic (2022).

data. In Section 6, we describe the results of the DDF estimation and the regression model of the factors behind the MAC. Section 7 concludes.

2. Carbon abatement in the chemical industry

This section describes the development of GHG emissions in the EU-28 chemical industry. Further, it describes the carbon abatement technologies available to the chemical sector for achieving carbon reduction targets.

The chemical sector consumes energy and raw materials to produce plastics, fibers, solvents, inorganic chemicals, fertilizers and various other types of products. A distinctive feature of the chemical sector is that it uses different types of energy carriers for both energetic purposes, as a source of power or thermal heat, and non-energetic (i.e., feedstock) purposes, as raw material input rather than as a source of energy (Boulamanti and Moya, 2017). About 75% of energy and non-energy use is used in large upstream production processes producing certain products, such as olefins (ethylene, propylene and butadiene), aromatics (benzene, toluene and xylene), ammonia, methanol and carbon black (Saygin and Gielen, 2021).

The transformation of energy and raw materials into products results in direct and indirect emissions. Direct emissions come from sources directly owned or controlled by the firm (Scope 1 GHG emissions) and can be divided into two sources, including the emissions from the combustion of fuels (combustion-related emissions) and the emissions generated from chemical transformations of raw materials consumed for non-energy use (process-related emissions). Indirect emissions come from assets not owned or controlled by the firm and either relate to the emissions from purchased electricity, steam, heat or cooling (Scope 2 GHG emissions) or those from the release of embedded carbon in chemical products (Scope 3 GHG emissions). When energy carriers are used for non-energetic purposes, part of the CO_2 becomes embedded in the chemical products. The embedded carbon is released during the end-of-life treatment of these products during product use or waste treatment (e.g., energy recovery). While half of the (global) chemical sector's energy input is consumed as feedstock (IEA, 2021), resulting in significant Scope 3 GHG emissions, this study only considers Scope 1 GHG emissions to avoid issues related to carbon accounting.

In the period between 1990 and 2020, the EU-28 chemical industry has reduced its' absolute Scope 1 GHG emissions by about 60%, while simultaneously expanding production by 42%, indicating a decoupling of production growth and GHG emissions (see Fig. 1). This emission reduction has mainly been the result of reductions in process-related nitrous oxide (N_2O) and fluorinated gas emissions (see Fig. 2) and improvements in energy efficiency, such as the implementation of combined heat and power and continuous process improvements. Over the same period, both fuel combustion-related and absolute CO_2 emissions decreased to a lesser extent, while no significant reductions in GHG emissions have been observed after 2013 (see Fig. 3).

From the techno-economic literature, we find various abatement options for carbon abatement available in the chemical sector (Saygin and Gielen, 2021). These options can be divided into the following categories: energy efficiency improvements, fuel switching, feedstock switching, circular economy concepts, carbon capture and storage (CCS), and shifting to low-carbon electricity. In Fig. 4, we describe the 20 carbon abatement options with their corresponding abatement cost range as derived from Saygin and Gielen (2021).[4]

3. Literature on estimating marginal abatement cost

There are three broad categories of methods to derive the marginal abatement cost (MAC) of a decision-making unit (DMU), including (1) expert-based evaluations, (2) model-derived methods, and (3) production-based methods (Kesicki, 2010; Kesicki and Strachan, 2011; Du et al., 2015).

Expert-based MACs are derived based on the assumptions of experts on the carbon abatement potential and costs of various abatement technologies (e.g., see Nauclér and Enkvist, 2009; Kesicki, 2010). While this method contains high technological detail, it is criticized for neglecting system-wide interactions, interactions between abatement measures (with the risk of double counting reduction potentials), transaction costs, and behavioral aspects (Kesicki and Strachan, 2011; Du et al., 2015).

Model-derived MACs are calculated using bottom-up or top-down models of the energy system. Bottom-up models are partial

[4] Maddedu et al. (2020) covers a more extensive assessment of technologies for the direct electrification of production processes, but does not report the associated abatement cost. According to Maddedu et al. (2020), all energy consumption for heating and cooling in the chemical sector can be electrified directly, in potential reducing 62% of the sector's Scope 1 GHG emissions. When also including the energy demand for feedstock, the electrification potential reduces to 23%. If electricity cannot substitute for fossil fuels, in the case of chemical feedstock, indirect electrification via synthetic fuels can be a low-carbon alternative to reduce end-of-life emissions.

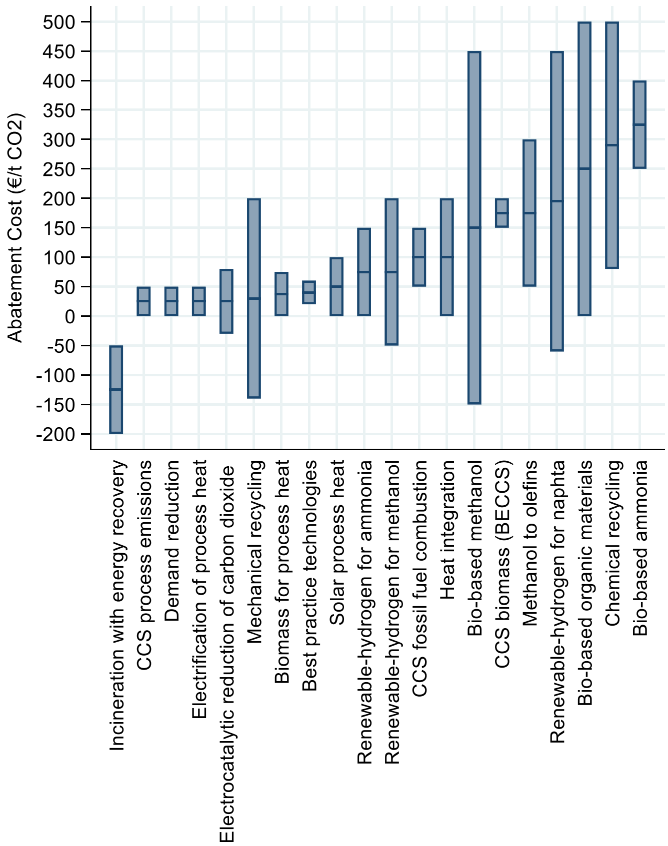

Fig. 4. The estimated abatement cost range for different technology alternatives for carbon emission abatement in the chemical industry (in €/t CO_2 using a 1 USD = 1 EUR exchange rate). Note: The bars depict the lower and upper bounds, as well as the mean value of the abatement cost per technology. The ranking of technologies is based on the mean abatement cost. Source: Saygin and Gielen (2021).

equilibrium models representing an energy system or sector, and are based on engineering approaches that model energy technologies explicitly (e.g., see Criqui et al., 1999; Loughlin et al., 2017). Top-down models are general equilibrium models covering the economy-wide production activities of different economic sectors, and the interactions between these (e.g., see Ellerman and Decaux, 1998; Klepper and Peterson, 2006). In both types of models, MACs are derived by applying incrementally increasing carbon prices and recording the corresponding emission levels, or vice versa, by defining emission reduction levels and deriving the carbon prices (Loughlin et al., 2017). While these types of models account for interactions between abatement technologies and across time, the drawback of these models is that these lack technological detail and that outcomes are sensitive to the underlying modeling assumptions (Du et al., 2015).

Production-based methods rely on production theory, which assumes that the DMU employs a production technology to produce a combination of desirable and undesirable outputs, using a given set of inputs, subject to a set of technical and economic constraints. To mitigate the undesirable output, the DMU must allocate productive resources towards abatement activities, which increases costs and decreases profits. This constraint-induced cost can be interpreted as the opportunity cost of lowering the undesirable output, as noted by Du et al. (2015).

Production-based methods include the cost function approach and the distance function approach. The cost function approach develops cost functions directly from cost data. Cost functions describe the relation between the cost of reducing emissions and a set of associated factors, such as emission levels and input factor prices, under the assumption of cost minimization. The cost function method calculates the MAC by constructing a cost function and taking the first order derivate with respect to emission levels to obtain the marginal cost function or by specifying the marginal cost function directly (Du et al., 2015). A drawback of the cost function method is that cost information is usually difficult to obtain, as it often is confidential information. In addition, in cases where firms have public aspects, such as utilities, cost minimization does not necessarily drive firm decisions (Matsushita and Yamane, 2012).

The distance function (DF) approach is an alternative method to model the environmental production technology that offers several advantages over the cost function when estimating the shadow price of the undesirable output. First, the distance function requires no information on input and output prices, which is often unavailable, to calculate shadow prices. Second, the duality between distance and cost functions allows for estimating the MAC relying only on information on input and output quantities. Third, the distance function requires no behavioral assumptions, such as cost minimization or revenue maximization (Matsushita and Yamane, 2012). Further, compared to the other methods described above, the DF method does not require making assumptions about future economic and technological developments or specifying of a functional form (Ji and Zhou, 2020).

The DF method commonly applies the (radial) Shephard distance function or the (non-radial) directional distance function (DDF) to model the environmental technology, which can both be input or output-oriented (Shephard, 1970; Färe et al., 1993; Chung et al., 1997). The main difference between the two is that the Shephard function expands both desirable and undesirable outputs proportionally, which is not ideal in the cases where undesirable outputs are not supposed to increase, whereas the DDF allows for both proportional and non-proportional changes in a particular direction for each output in order to reach the efficient frontier (Chung et al., 1997; Färe et al., 2005). This makes the DDF method more suitable for measuring DMU performance in the presence of undesirable output regulation, such as firms subject to carbon trading schemes.

Both parametric and non-parametric methods can be used to calculate the partial derivatives of the DF and obtain the shadow prices for the undesirable output. The non-parametric method usually refers to Data Envelopment Analysis (DEA), which constructs the production possibility set as a piecewise linear combination of all observed inputs and outputs (Du et al., 2015). Examples of studies estimating the MAC using the DEA approach include, among others, Choi et al. (2012) and Xie et al. (2017). An advantage of DEA is that it can measure the efficiency of DMUs without assuming a functional form for the production frontier (Charnes et al., 1978). However, due to the non-differentiability of the DF under the DEA approach, it is possible that some efficient observations are located on the inflection points or vertices, so that there are no unique slopes at those points (Ma and Hailu, 2016). As the main advantage of the parametric specification is that the estimated frontier is differentiable, we focus on the parametric specification of the DF.

The parameters of the parametric DF can be estimated using the deterministic linear programming (LP) model by Aigner and Chu (1968), which minimizes the sum of the deviations of the estimated DFs from their frontier under a given set of constraints, or by stochastic approaches based on stochastic frontier analysis (SFA). An advantage of the SFA method is that it accounts for statistical noise. However, a drawback is that SFA cannot incorporate constraints into the estimation and requires distributional assumptions for inefficiency and error terms.

In contrast, the LP method does not make distributional assumptions and allows for modeling the DF properties using inequality constraints. Previous studies have used the parametric DDF to estimate the MAC at the regional level (Du et al., 2015; Ma and Hailu, 2016; Ji and Zhou, 2020), at industrial level (Peng et al., 2012; Chen, 2013), for electric utilities (Matsushita and Yamane, 2012; Wei et al., 2013; Jain and Kumar, 2018), and firms in the iron and steel industry (Wang et al., 2017).

This paper contributes to the literature by estimating the MAC of firms in the European chemical industry. Using the parametric DDF method, we assume that the representative firm's abatement strategy is based on a good output-maximizing approach, which reflects the regulatory environment of energy-intensive industries in the EU-ETS. To validate the results of our DDF model, we compare our derived MACs to the carbon market price in the EU-ETS and information on the cost of various abatement technologies available in the chemical sector.

4. Method

This section describes the theoretical framework for the derivation of shadow prices using the directional distance function (DDF), the empirical specification of our DDF model and the choice for the directional vector used in the DDF. Further, we explain the firm-specific factors used in the regression analysis to explain the MAC to clarify our results.

4.1. Theoretical framework

We assume the production process of firms in the chemical sector employs inputs $x = (x_1, x_2, \ldots, x_N) \in R_+^N$ to produce desirable outputs $y = (y_1, y_2, \ldots, y_M) \in R_+^M$ and undesirable outputs $b = (b_1, b_2, \ldots b_J) \in R_+^J$. The production technology is represented by the output set $P(x)$ denoting the set of desirable and undesirable outputs (y, b) that can be jointly produced from the input vector x. More formally,

$$P(x) = \{(y, b) : x \text{ can produce } (y, b)\} \tag{1}$$

We impose the standard axioms on the output sets as described in Färe et al. (2005):

i. $P(x)$ is compact: $P(0) = (0, 0)$
ii. Strong disposability of inputs: $x \leq x'$ implies $P(x) \in P(x')$
iii. Strong disposability of desirable outputs: $(y', b) \leq (y, b)$ implies that $(y', b) \in P(x)$
iv. Weak disposability of outputs: if $(y, b) \in P(x)$, $0 \leq \theta \leq 1$, then $(\theta y, \theta b) \in P(x)$. This assumption states that only proportional contractions of desirable and undesirable goods are feasible for a given level of inputs, implying that reducing undesirable outputs is costly.
v. Null-jointness: if $(y, b) \in P(x)$ and $b = 0$, then $y = 0$. This assumption states that it is not possible to produce the desirable output without some undesirable output, that is, the undesirable output is a by-product.

We use the output-oriented DDF to represent the environmental technology set $P(x)$. Let $g = \left(g_y, -g_b\right) \neq 0$ be the directional vector. Then, the output DDF can be defined as the maximum amount by which the outputs can be adjusted along a certain directional vector:

$$\overrightarrow{D_0}(x, y, b; g) = \max\left\{\beta : \left(y + \beta g_y, b - \beta g_b\right) \in P\left(x\right)\right\} \tag{2}$$

where β is non-negative and scaled to reach the frontier of the output set $\left(y + \beta^* g_y, b - \beta^* g_b\right) \in P(x)$ with $\beta^* = \overrightarrow{D_0}(x, y, b; g)$. A positive β indicates that the firm is inefficient and a higher β points to a lower technical efficiency, implying that the firm is further away from the frontier. A zero value for β indicates that the firm is operating at the efficient frontier. The DDF satisfies the following properties from the output set $P(x)$:

i. Non-negativity: $\overrightarrow{D_0}(x, y, b; g) \geq 0$ if and only if $(y, b) \in P(x)$
ii. Monotonicity for the desirable output: $\overrightarrow{D_0}(x, y', b; g) \geq \overrightarrow{D_0}(x, y, b; g)$ for $(y', b) \leq (y, b) \in P(x)$
iii. Monotonicity for the undesirable output: $\overrightarrow{D_0}(x, y, b'; g) \geq \overrightarrow{D_0}(x, y, b; g)$ for $(y, b') \geq (y, b) \in P(x)$
iv. Weak disposability: $\overrightarrow{D_0}(x, \theta y, \theta b; g) \geq 0$ for $(y, b) \in P(x)$ and $0 \leq \theta \leq 1$,
v. Translation property: $\overrightarrow{D_0}\left(x, y + \alpha g_y, b - \alpha g_b; g\right) = \overrightarrow{D_0}(x, y, b; g) - \alpha$

To derive the shadow price of the undesirable output, we use the duality between the maximal revenue function and the directional output distance function (Färe et al., 2006). Let p represent the market price for the desirable output and $q = (q_1, \ldots, q_J)$ be a vector of undesirable output prices that are unobservable. Then, the revenue function is given by:

$$R(x, p, q) = \max_{y,b}\left\{py - qb : \overrightarrow{D_0}(x, y, b; g) = 0\right\} \tag{3}$$

where $\overrightarrow{D_0}(x, y, b; g) = 0$ is used as constraint so to only consider the frontier of the production possibility set. To solve the maximization problem above and derive the shadow price function, we use the Lagrangian method. The Lagrangian function for (3) can be expressed as:

$$L = py - qb + \lambda \overrightarrow{D_0}(x, y, b; g) \tag{4}$$

From the first order conditions with respect to y and b, we obtain

$$\frac{\delta L}{\delta y} : p + \lambda \frac{\delta \overrightarrow{D_0}(x, y, b; g)}{\delta y} = 0 \tag{5}$$

$$\frac{\delta L}{\delta b} : -q + \lambda \frac{\delta \overrightarrow{D_0}(x, y, b; g)}{\delta b} = 0 \tag{6}$$

We derive the shadow price of the undesirable output (q) as follows:

$$q = -p\left[\frac{\delta \overrightarrow{D_0}(x, y, b; g) \Big/ \delta b}{\delta \overrightarrow{D_0}(x, y, b; g) \Big/ \delta y}\right] \tag{7}$$

where shadow price q represents the value of desirable output foregone to reduce the undesirable output with one unit for a DMU operating at the efficient frontier (the so-called marginal rate of transformation between the desirable and the undesirable output).

For illustration purposes, Fig. 5 describes how the DDF measures the efficiency of DMUs in the case of one desirable output (y) and one undesirable output (b) under different specified directional vectors (g). In the figure, DMU C is located under the boundary of the production possibility set $P(x)$, which implies that DMU C's production process is inefficient compared to its' peers. Efficiency can be defined along any specified directional vector from point C towards the efficient frontier

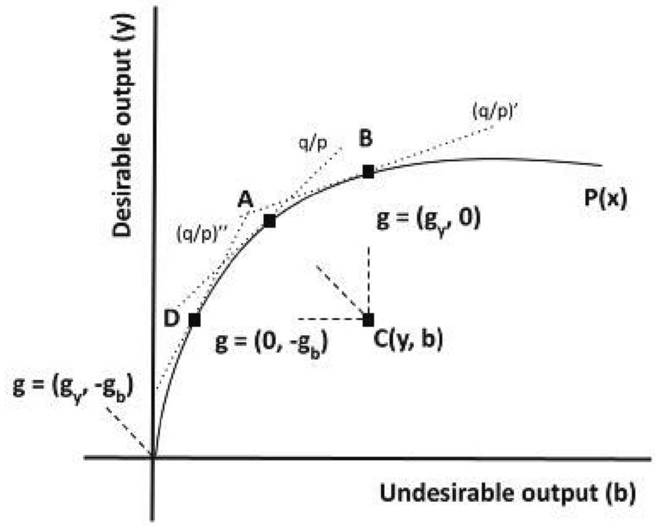

Fig. 5. Distance functions. Note: $P(x)$ denotes the output set, y is the desirable output, b is the undesirable output, p is the price of the desirable output, q is the shadow price of the undesirable output, $\frac{q}{p}$ is the relative shadow price, g represents a directional vector. Points A, B, C, and D represent DMUs.

(for example, towards DMUs A, B, or D). The directional vector $g = \left(g_y, -g_b\right)$ describes the simultaneous unit expansion of the desirable output and the unit contraction of the undesirable output in the production function. Alternatively, we can assume the desirable and undesirable outputs are treated asymmetrically. The vector $g = \left(g_y, 0\right)$ describes a situation in which the desirable output is allowed to expand while the undesirable output is held constant. In this case, the inefficient firms move vertically to the efficient frontier to gain maximum good output for a given amount of undesirable output. The vector $g = (0, -g_b)$ holds the desirable output constant while contracting the undesirable output. Here, the inefficient firms move horizontally to the efficient frontier to gain minimum undesirable output for a given amount of desirable output.

The slopes of the lines tangent to the points of the efficient DMUs represent the relative shadow prices for output bundle C(y, b). As denoted by Eq. (7), the relative shadow price equals the ratio of the partial derivatives of the distance functions with respect to both outputs. A vertical directional vector favoring the expansion of the desirable output relates to a relatively low slope equal to (q/p)' in Fig. 5, whereas a horizontal vector favoring the reduction of the undesirable output relates to relatively large slope equal to (q/p)". The vertical and horizontal vectors, given by $g = (1, 0)$ and $g = (0, -1)$, represent the lower and upper boundaries of the relative shadow prices in the DDF (Wei et al., 2013; Wang et al., 2017).

4.2. Empirical specification

We use the deterministic LP model by Aigner and Chu (1968) to compute the unknown parameters in the parametric DDF. Frequently used functional forms for the parametric specification include translog and quadratic functions (Zhou et al., 2014). Contrary to the translog form, the quadratic form can be specified to satisfy the translation property (Färe et al., 2006). In addition, previous literature has indicated that quadratic models outperform translog models under various conditions (Färe et al., 2008; Vardanyan and Noh, 2006; Matsushita and Yamane, 2012). Therefore, we specify the quadratic function to parameterize the DDF.

Previous studies have argued for using a multi-pollution framework, modeling multiple undesirable outputs in the production technology to obtain conditional MAC estimates rather than unconditional MAC estimates obtained from modeling a single undesirable output (Ma and Hailu, 2016; Ji and Zhou, 2020). To estimate the overall compliance cost of pollutant mitigation, the conditional MAC is more informative, as mitigating a given pollutant (e.g., carbon dioxide) has often the co-benefit of mitigating other correlated pollutants in the mitigation process, such as sulfur dioxide, methane, or nitrous oxide. Due to data availability, we model a single pollution model, instead of modeling a multi-pollution model, using a single metric covering different types of GHGs (see footnote 5).

Suppose each firm in the European chemical sector employs three inputs, namely labor (x_1), capital (x_2) and energy consumption (x_3), to produce a desirable output, revenue (y), and an undesirable output, carbon emissions (b). Then, the quadratic DDF for firm i in year t can expressed as:

$$\overrightarrow{D_0}(x_{it}, y_{it}, b_{it}; g) = a_0 + \sum_{n=1}^{3} a_n x_{nit} + \frac{1}{2}\sum_{n=1}^{3}\sum_{n'=1}^{3} a_{nn'} x_{nit} x_{n'it} + \beta_1 y_{it} + \frac{1}{2}\beta_{11} y_{it}^2 + \gamma_1 b_{it} + \frac{1}{2}\gamma_{11} b_{it}^2 + \Sigma_{n=1}^{3}\delta_n x_{nit} y_{it} + \Sigma_{n=1}^{3}\eta_n x_{nit} b_{it} + \mu y_{it} b_{it} \tag{8}$$

where a_0, a_n, $a_{nn'}$, β_1, β_{11}, γ_1, γ_{11}, δ_n, η_n, and μ_1 are the unknown parameters to be estimated for n and $n' = 1,2,3$. Then, the shadow price (or MAC) is calculated by taking the derivative of Eq. (8) with respect to the desirable and undesirable outputs and substituting the result into Eq. (7):

$$\delta \overrightarrow{D_0}(x_{it}, y_{it}, b_{it}; g) \Big/ \delta y_{it} = \beta_1 + \beta_{11} y_{it} + \Sigma_{n=1}^{3} \delta_n x_{nit} + \mu b_{it} \tag{9}$$

$$\delta \overrightarrow{D_0}(x_{it}, y_{it}, b_{it}; g) \Big/ \delta b_{it} = y_1 + \gamma_{11} + \Sigma_{n=1}^{3} \eta_n x_{nit} + \mu y_{it} \tag{10}$$

$$q = -p\left[\frac{y_1 + \gamma_{11} + \Sigma_{n=1}^{3} \eta_n x_{nit} + \mu y_{it}}{\beta_1 + \beta_{11} y_{it} + \Sigma_{n=1}^{3} \delta_n x_{nit} + \mu b_{it}}\right] \tag{11}$$

Considering the various chemical products of the chemical firms in our sample, we use the monetary output value of these firms rather than the physical outputs as desirable outputs (Wang et al., 2017). This implies that p represents the market price of revenue, which is a monetary measure of goods and services produced with a value of 1. In this case, the shadow price is interpreted as the value of revenue foregone to reduce carbon emissions with one unit for a firm operating at the efficient frontier.

The deterministic LP method by Aigner and Chu (1968) is used to estimate the unknown parameters on the right-hand side of the quadratic DDF in Eq. (8). The LP method estimates the parameters by minimizing the sum of the deviations between the individual firm observations and the frontier in each year, subject to the constraints satisfying the underlying restrictions of the DDF. Following Ji and Zhou (2020), we define the directional vector as $g = \left(g_y, g_b\right) = (\sigma, -\nu)$. Then, the LP model can be denoted as follows:

$$min \Sigma_{i=1}^{I} \Sigma_{t=1}^{T} \left[\overrightarrow{D_0}(x_{it}, y_{it}, b_{it}; g) - 0\right]$$

subject to

i. $\overrightarrow{D_0}(x_{it}, y_{it}, b_{it}; g) \geq 0,\ i = 1, \dots, I,\ t = 1, \dots, T$

ii. $\delta \overrightarrow{D_0}(x_{it}, y_{it}, b_{it}; g) / \delta y_{it} \leq 0$

iii. $\delta \overrightarrow{D_0}(x_{it}, y_{it}, b_{it}; g) / \delta b_{it} \geq 0$

iv. $\alpha_{nn'} = \alpha_{n'n}$ for $n \neq n'$

v.

$$\sigma\beta_1 - \nu\gamma_1 = -1; \sigma\beta_{11} = \nu\mu; \sigma\mu = \nu\gamma_{11}; \sigma\Sigma_{n=1}^{3}\delta_n = \nu\Sigma_{n=1}^{3}\eta_n \tag{12}$$

Restriction (i) ensures that all observations are feasible and located either on or below the frontier; (ii) and (iii) ensure negative monotonicity and positive monotonicity in the desirable and undesirable outputs, respectively; (iv) impose the symmetry conditions; and (v) imposes the translation property of the DDF which depends on the specification of the directional vector.

4.3. Choice of directional vector

The directional vector used in the DDF represents the different production and emission abatement strategies of the DMUs. From the literature, it can be inferred that the estimated shadow prices of undesirable outputs are sensitive to the directional vector used in the DDF estimation (Vardanyan and Noh, 2006; Wang et al., 2017; Jain and Kumar, 2018; Ji and Zhou, 2020). For the directional vector $g = (\sigma, -\nu)$, the ratio of ν to σ indicates the relative importance of the desirable and undesirable output in the production technology, and reflects the long-term growth pattern of the DMU. In general, as the ratio $\frac{\nu}{\sigma}$ increases, the shadow price for the undesirable output increases. This implies that when the production technology is on a growth path that favors reducing carbon emissions, the MAC of carbon emissions is higher (Baker et al., 2008; Ji and Zhou, 2020).

We impose the directional vector to be reflective of the regulatory environment of EU energy-intensive industries. That is, we assume our directional vector reflects the European chemical sector's imposed requirement to reduce relative emissions (i.e., the carbon intensity), rather than absolute emissions, in the period under consideration. Under the EU-ETS, industrial installations considered to be at significant risk of carbon leakage receive a significant share of their total emission allowances for free. Since the start of phase 3 of the EU-ETS (2013–2020), the free allocation of emission allowances is based on relative benchmarks determined by historical production data (EC, 2021).[5] More specifically, the amount of freely allocated allowances is determined by the average CO_2 emissions per unit of production of the 10% most efficient installations in a given benchmark group. Based on this average carbon intensity, each sub-installation in a certain benchmark group receives the same number of emission allowances per unit of production. This implies that, in principle, efficient installations do not need to purchase additional allowances as they receive sufficient allowances needed to cover their emissions, whereas installations emitting above the benchmark need to purchase additional allowances to cover their emissions, incentivizing inefficient installations to alter their carbon intensity per unit of production. Further, we assume firms follow the least-cost pathway to reduce their carbon intensities.

Following the above, we assume a directional vector of $g = (\sigma, -\nu) = (1, 0)$. This implies that firms in our sample follow a good output maximizing-approach, where the growth path gives priority to revenue growth while simultaneously holding the level of carbon emissions constant. Under a good output-maximizing approach, firms are evaluated in the direction of the desirable output (y), firm-level revenue. Therefore, given the assumed directional vector, efficient firms have no peers with higher levels of the desirable output for a given level of inputs (x) and undesirable output (b), while inefficient firms need to increase their desirable output by a given proportion to reach the efficient frontier.[6]

4.4. Explaining the MAC

To explain our results, we make use of the fact that the MAC can be written as a function of firm-specific variables, including firms' carbon intensity, energy intensity, capital intensity, and market capitalization.

Carbon intensity is defined as the ratio of carbon emissions to energy consumption (in t CO_2/MWh) and is expected to be negatively related to the MAC, as carbon-intensive firms are expected to have more low-cost abatement opportunities (Wei et al., 2013; Du et al., 2015; Jain and Kumar, 2018).

Energy intensity is defined as the amount of energy consumed to produce a given level of output and is calculated as the ratio of energy consumption to revenues (in kWh/€). We expect a negative relationship between energy-intensity and the MAC, as firms with relatively high energy consumption have greater scope for abating carbon emissions in order to improve energy efficiency (Du et al., 2015). The more energy-efficient (and less energy-intensive) the firm becomes, the higher the MAC, as more expensive abatement options are exercised. However, we note that a firm's energy-intensity does not necessarily inform us about the type of energy consumption and the scope for additional abatement within the firm. For some firms, energy consumption can be relatively less carbon-intensive compared to other firms, implying a higher MAC, while energy consumption is relatively high. In the latter case, the negative relationship between energy intensity and the MAC is not evident.

Market capitalization (in billion EUR) is included to control for firm

[5] European Commission (2021). Update of benchmark values for the years 2021–2025 of phase 4 of the EU-ETS.

[6] Note that an abatement strategy following an undesirable output minimizing approach, which favors the reduction of carbon emissions, is not the preferred strategy to reduce carbon intensity and reach the efficient frontier, as a higher ratio of ν to σ results in higher abatement cost to the firm. Therefore, we do not consider the directional vector $g = (\sigma, -\nu) = (0, -1)$.

Table 1
Descriptive statistics of 24 chemical firms for the period 2015–2020.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Revenue (billion EUR)	144	8.45	12.26	0.30	70.45
CO_2-emissions (in 10^3 tons)	144	3413.28	5314.65	5.57	17,820
Labor (in 10^3 employees)	144	18.93	24.71	0.74	122.40
Capital (billion EUR)	144	4.19	5.65	0.02	26.41
Energy consumption (million MWh)	144	20.48	33.89	0.04	192.10

Source: Bloomberg (2021).

size, as carbon mitigation is often characterized by economies of scale (Wei et al., 2013; Jain and Kumar, 2018). Larger firms can benefit from economies of scale in resource utlization and pollution abatement, and are therefore expected to have a lower MAC (Dasgupta et al., 2001; Wei et al., 2013; Jain and Kumar, 2018).

5. Data

We construct a balanced panel dataset consisting of 24 firms active in the European chemical sector from 2015 to 2020.[7] Each firm in our sample has production facilities in EU and, therefore, some or all installations directly owned or controlled by each firm fall under the scope of the EU Emissions Trading System (EU-ETS), which is a cap-and-trade system operating in all EU countries plus Iceland, Liechtenstein and Norway (EEA-EFTA states). Table A.1 in Appendix A lists the names and corresponding subsectors of the firms in our dataset.

The data on our three inputs (labor, capital and energy), desirable output (revenue), undesirable output (CO_2 emissions) are obtained from Bloomberg and firms' annual reports. Table 1 describes the summary statistics of our variables and Table A.1 in Appendix A describes the mean values for revenue, CO_2-emissions, labor, capital, and energy consumption per firm. As a measure of firms' desirable output, we use the amount of revenue (i.e., net sales) in EUR generated from firm operating activity after the deduction of sales returns, allowances, discounts, and sales-based taxes. This reflects the firm's aim to maximize the direct value of produced goods or services. For the undesirable output we use firm-level data on Scope 1 emissions reported in thousands of metric tons of CO_2-equivalents covering emissions of the most important GHGs[8] Scope 1 emissions fall under the direct control of the firm, which allows us to identify heterogeneity in firms' production processes (Trinks et al., 2020). In contrast, Scope 2 and 3 emissions can be altered without long-term changes to production activities within the firm (Trinks et al., 2020). Firms' labor input is measured as the number of people employed by the firm, which is based on the number of full-time equivalents (and if unavailable, the number of full-time employees). As a measure of the firms' capital stock, we use the book value of property, plant, and equipment (PPE, or Net Fixed Assets) in EUR, which represents the firms' physical capital used for operating activities. Energy consumption is a measure of the amount of energy in MWh directly consumed by the firm through combustion in owned or controlled boilers, furnaces, vehicles, or through chemical production in owned or controlled process equipment. It also includes energy consumed as electricity.

6. Results

6.1. Shadow price estimation

We estimate the parameters of the DDF using the deterministic linear programming (LP) method by Aigner and Chu (1968). To avoid convergence problems, the data are normalized by dividing each input and output by its mean value (Färe et al., 2005). We include firm and year dummies to control for time-invariant firm effects and time effects in the production technology (Färe et al., 2005; Du et al., 2015; Ji and Zhou, 2020). We omit the dummies for the year 2015 and firm 1 to avoid the dummy variable trap. We estimate the shadow prices using Eq. (7). Given that all input and output data are normalized, we multiply Eq. (11) with $mean(y)/mean(b)$.

Following the shadow price estimation with the assumed directional vector, we test if the null-jointness assumptions holds across all observations. The null-jointness assumption states that desirable and undesirable outputs are jointly produced, which implies that a combination of positive revenues and non-positive carbon emissions is not part of the production possibility set (i.e., $(y,0) \notin P(x)$). Further, we recall from the restrictions in method Section 4 that $(y,b) \in P(x)$ only if $\overrightarrow{D_0}(x_{it}, y_{it}, b_{it}; g) \geq 0$. This implies that observations satisfy the null-jointness assumption if it holds that $y > 0$, $b = 0$ and $\overrightarrow{D_0}(x_{it}, y_{it}, b_{it}; g) < 0$. In Table 2, we report the share of observations satisfying the null-jointness assumption, the mean and median DDF values, and the goodness-of-fit of the LP model.[9] Further, we report the calculated parameters of the DDF in Table A.2 in Appendix A.

Table 3 summarizes our technical efficiency and shadow price estimates and Table A.3 in Appendix A describes the summary statistics of the estimated shadow prices per firm. We exclude 16 observations in total, as 16 observations contain negative values for the frontier values of b_j $(b_j - \widehat{\beta})$. For the remaining 128 observations, we find that 12 observations have zero inefficiency, which indicates these points are operating on the efficient frontier. Under the assumed directional vector, we find a median inefficiency of 0.0395 and a median shadow price of 429 €/t CO_2. The shadow price varies between 0 and 477 €/t CO_2. Given the data normalization and our directional vector, these results indicate that, at the median, firm revenue can be increased by 0.0395 × € 8.45 billion = € 333.78 million, while carbon emissions remain constant, if all firms would operate efficiently. Therefore, the CO_2 intensity of revenue (in kg CO_2/€) of European chemical firms can be reduced from 0.404 to 0.388 kg CO_2/€, resulting in a reduction of carbon intensity of 3.96%. At the mean inefficiency level, the average firm revenue could be further increased, while carbon emissions remain

[7] The Industrial Classification Benchmark (ICB) divides the firms into four subsectors (with the number of firms per subsector between parentheses): Chemicals and Synthetic Fibers (1), Chemicals Diversified (12), Fertilizers (3) and Specialty Chemicals (8). Given the different subsector classifications, there might be substantial firm heterogeneity in the production technologies across firms in our dataset. For example, firms might structurally differ based on their technologies and capacities, equipment, customer and product portfolio's, factor cost differences, and regulatory environments. The heterogeneity in production technologies implies that the inter-factor substitutability between firms is limited in the short-run (Ma and Hailu, 2016). However, this is consistent with the DDF, which assumes more drastic inter-factor substitutions in the long-run. This study estimates the MAC for the whole sample of firms and does not further explore the heterogeneity in production technologies across firms, for which the meta-frontier distance function may be a possible alternative (Zhang et al., 2013).

[8] Scope 1 emissions refer to the firm's direct GHG emissions, from sources directly owned or controlled by the firm, such as boilers, furnaces, vehicles, or chemical process equipment. Scope 2 emissions refer to indirect GHG emissions from purchased electricity, steam, heat or cooling. Scope 3 emissions include other indirect GHG emissions released in the firms' value chain, which result from activities from assets not owned or controlled by the firm.

[9] Following Ji and Zhou (2020), the goodness-of-fit criterion (Ω) is defined as $\Omega = \frac{\Sigma_{i=1}^{I}\Sigma_{t=1}^{T} n_{it}/N}{\Sigma_{i=1}^{I}\Sigma_{t=1}^{T}\left(\widehat{\overrightarrow{D_0}}(x_{it}, y_{it}, b_{it}; g) - 0\right)/N}$, where $N = I^{*}T$, $n_{it} = \begin{cases} 1, \text{if } \widehat{\overrightarrow{D_0}}(x_{it}, y_{it}, b_{it}; g) < 0 \\ 0, \text{otherwise} \end{cases}$, and $\widehat{\overrightarrow{D_0}}(x_{it}, y_{it}, b_{it}; g)$ is the estimated value for each DDF. The numerator represents the share of observations satisfying the null-jointness assumption and the denominator the arithmetic mean of the estimated DDF values.

Table 2
Goodness-of-fit results.

Directional vector	Observations	Share of observations satisfying the null-jointness assumption	Mean of estimated DDF values	Median of estimated DDF values	Goodness-of-fit criterion (Ω)
DDF (1, 0)	144	0.5208	0.105	0.0278	4.935

Note: 24 firms and 3 inputs (capital, labor, and energy).

Table 3
Inefficiency and shadow price estimates.

Variable	Observations	Mean	Median	Std. Dev.	Min.	Max.	Number of frontier observations
Inefficiency ($\widehat{\beta}$)	128	0.1187	0.0395	0.217	0.00	1.71	12
Shadow price of CO_2 (€/tCO_2)	128	369.54	428.80	119.45	0.00	477.13	–

Note: 16 observations contain negative vale for the frontier value of b_j ($b_j - \widehat{\beta}$). Hence, we exclude these 16 observations from the estimates.

constant, reducing the carbon intensity of the industry by 10.61% if all firms would operate efficiently.

For illustrative purposes, Fig. 6 depicts the distribution of estimated shadow prices (in €/t CO_2) across all observations, while Fig. 7 depicts the distributions of the estimated shadow prices per firm. The estimated shadow prices fall within the range of abatement costs (−200 to 500 €/t CO_2) for the technologies featured in Fig. 4. This suggests that some firms have access to less expensive abatement technologies on the left-hand side of Fig. 4, while others can only reduce their carbon emissions through methods that are more expensive. For instance, firms with relatively low marginal abatement costs, such as YARA, AIR LIQUIDE and BASF, can use the more affordable technologies like the electrification of process heat, solar process heat, or CCS of process emissions. In contrast, the firms with higher marginal abatement costs, such VICTREX, GIVAUDAN and JOHNSON MATTHEY, can only reduce their emissions by using more costly methods, such as renewable hydrogen, chemical recycling or using bio-based organic materials as feedstock.

To assess the temporal change in shadow prices during the estimation period, we plot the kernel density curves of the MACs in Fig. A.1 in Appendix A. Although the direction of the shift of the curves over the years is not immediately evident, the yearly means demonstrate a decreasing trend in the MACs, indicating a leftward shift in the kernel density curves. A leftward shift of the kernel density curves over time indicates that the marginal costs to abate CO_2 emissions have decreased over time, potentially due to technological innovation or learning effects that have lowered the cost of adopting certain abatement technologies (e.g., the cost of renewable electricity generation has decreased over time).

6.2. Comparison shadow price with external benchmark

We follow previous literature by comparing our derived shadow prices to the actual market prices for carbon allowances in the period 2015–2020 (Wei et al., 2013; Ma and Hailu, 2016; Ma et al., 2019; Ji and Zhou, 2020).[10]

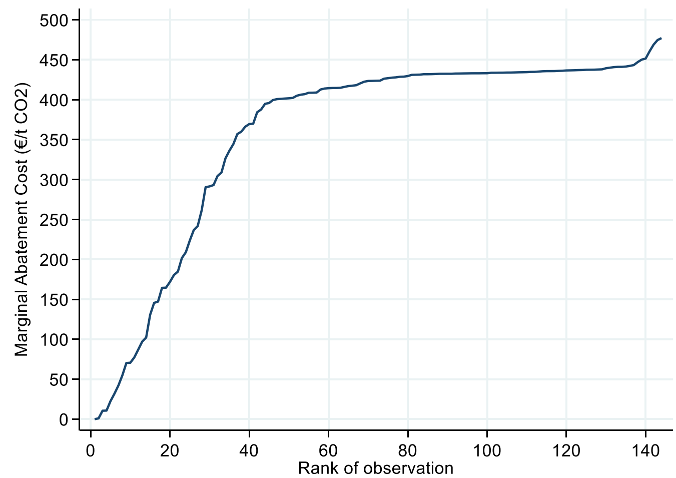

Fig. 6. Estimated shadow prices (in €/t CO_2) ranked from low to high for all 144 observations in the period 2015–2020.

Under the assumed directional vector, we observe that for most observations in the sample our derived shadow prices exceed the carbon market price range in this period (i.e., 7–30 €/t CO_2), whereas only the lower end of MAC estimates is close to observed market prices. For 13 of the 144 observations in our sample, the MAC is lower than an EU allowance price of 100 €/t CO_2 which indicates these may benefit from mitigating emissions within the firm and selling excess allowances on secondary markets. For most observations, the MAC is higher than 100 €/t CO_2. Therefore, these firms either receive free allowances in primary allocations or need to buy their allowances on secondary markets, rather than abate emissions within the firm. In the case of relatively high shadow price estimates, firms can achieve gains in economic efficiency through the purchase of emission allowances on secondary markets, instead of abating themselves. This does not hold for the firms with relatively low shadow prices, which gain by abating emissions within the firm rather than by buying emission allowances on secondary markets.

The divergence between our MAC estimates and observed market carbon prices can be explained as follows. First, relative to non-radial DFs (DDF), radial DFs (Shephard DFs) are more likely to provide short-run MAC estimates which are directly comparable to market prices for carbon allowances (Ma and Hailu, 2016; Ma et al., 2019). This is because radial and non-radial DFs project the input and output vector onto the production possibility frontier in different ways. In case of radial DFs, the input and output mix is kept fixed at current proportions, while non-radial DFs do not preserve the current mix of

[10] The estimated MACs can be interpreted as the value of a carbon emission allowance in a carbon market (Coggins and Swinton, 1996; Ma et al., 2019). Therefore, the carbon market price can be used as benchmark for the estimated MACs to assess the validity of the DDF specification and other parameters in the estimation (Ma et al., 2019). Although the carbon market price is an appropriate benchmark, it is not identical to the shadow price as the former is determined by the supply and demand for allowances of all market players that fall under the scope of the EU-ETS, while the latter reflects an opportunity cost of the individual DMU (Coggins and Swinton, 1996; Smith et al., 1998; Wei et al., 2013; Du et al., 2015).

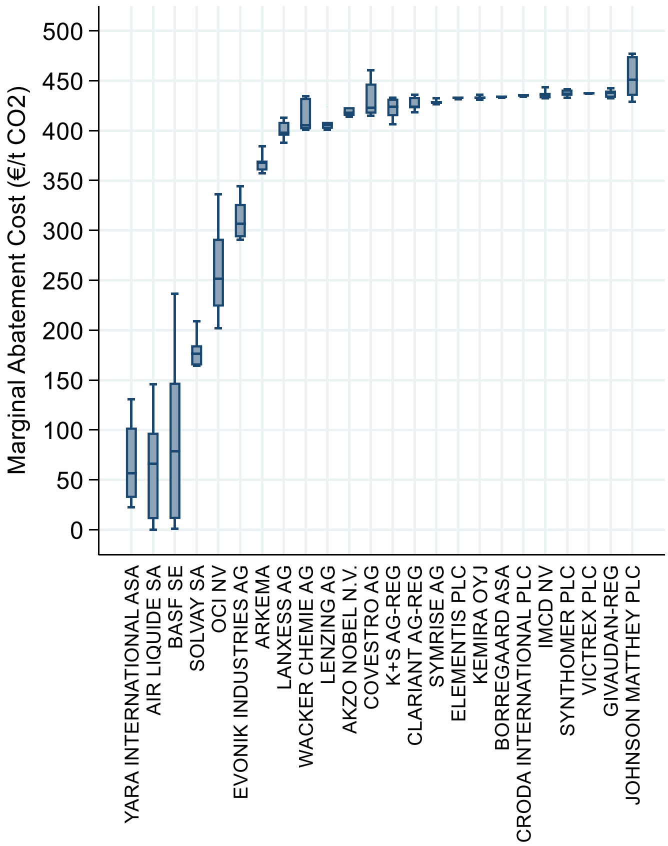

Fig. 7. Distribution of estimated shadow prices (in €/t CO_2) per firm ranked by firms' average abatement cost over the period 2015–2020.

inputs and outputs when projecting to the frontier. Given that the elasticity of inter-fuel and inter-factor substitution is greater in the long run than in the short run, significant transformations in the input or output mix are more likely to occur in the long run than in the short run. As significant long run transformations are expected to be more costly, we expect higher estimated MAC in case of non-radial DFs.

Second, the market carbon price is determined by the supply and demand for allowances of all market players that fall under the scope of the EU-ETS, while the MAC reflects the opportunity cost of abatement of the individual DMU. As the chemical sector is only partly determining the total supply and demand for carbon allowances in the EU-ETS, the derived shadow prices from our sample do not necessarily need to equal the market price for carbon. The observed market price for carbon reflects the MAC of those firms trading allowances on secondary markets, which are typically firms with low abatement costs (Ma et al., 2019). For relatively modest mitigation targets in carbon trading markets, requiring relatively less abatement compared to stringent targets, firms with higher MACs would not need to abate, whereas only the firms with lower MACs undertake the actual abatement activities.

6.3. Explaining the MAC

We start by exploring the relationship between the MAC and each of the explanatory variables by graphing a Locally Weighted Scatterplot Smoothing (LOWESS) of the estimated marginal abatement costs (in €/t CO_2) on carbon intensity (t CO_2/MWh), energy intensity (kWh/€), market capitalization (in billion EUR), and carbon emissions (in Mt. of CO_2) using the default brandwith of 0.8 and a tricube weight function

Table 4
Regression model results.

Dependent variable: MAC	
Carbon intensity	−516.69**
	(242.17)
Energy intensity	−9.34
	(11.38)
Market capitalization	−4.54**
	(1.85)
Year	
2016	19.55*
	(10.17)
2017	6.91
	(7.33)
2018	−16.77**
	(7.18)
2019	−5.21
	(8.04)
2020	−1.61
	(10.93)
Constant	516.66***
	(34.19)

Note: Standard errors in parentheses. Significance levels are indicated by ***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$. Bootstrap replications: 200.

(see Fig. A.2 in Appendix A). Overall, we observe a negative relationship between the MAC and the explanatory variables, indicating that it is more costly to reduce emissions at the margin when these variables have lower values, as was hypothesized.

Finally, we conduct a linear regression to estimate the impact of the variables on the MAC curve. As independent variables, we use firms' carbon intensity, energy intensity and market capitalization. We control for year effects by including dummy variables. As our dependent variable is an estimate that is based on a previous estimation, we bootstrap the standard errors to account for potential estimation errors.

From Table 4, we find that the coefficient of carbon intensity is significant at the 5% level and negatively related to the MAC. We find that for each 0.1 unit increase in the carbon intensity (in t CO_2/MWh), the MAC decreases with 51.67 €/t CO_2. This indicates that less carbon-efficient (and more carbon-intensive) firms have lower MACs, implying there are relatively more low-cost abatement options that are not yet exercised. Further, we find that the coefficient of market capitalization is significant at the 5% level and negatively related to the MAC. For every unit increase in the market capitalization (in billion EUR), the MAC decreases with 4.54 €/t CO_2. This implies that larger firms have relatively more low-cost abatement options, which is a finding consistent with previous empirical studies (Wei et al., 2013; Wang et al., 2017; Jain and Kumar, 2018).

7. Conclusions

To achieve carbon mitigation targets, all industries need to invest in additional carbon abatement measures, including the chemical industry, which is responsible for about 3.5% of the aggregated GHG emissions in Europe. There are various abatement technologies available to this industry to address the energy and carbon emission intensity of production processes and fuel combustion. This study estimates the marginal cost of abatement on firm level and compares these results to information on the costs of abatement technologies as well the benchmark of the carbon price in the EU-ETS.

We derive the MAC by evaluating firms' carbon intensity levels relative to those of efficient peers with comparable production activities. More specifically, we use a quadratic directional output distance function (DDF) model under the assumption that firms' carbon abatement strategies are based on a good output-maximizing approach. This approach allows for the expansion of the desirable output while the carbon emissions remain constant. This approach is consistent with actual climate policies for industries that use relative-emission benchmarks.

For a sample of 24 firms in the European chemical sector over the years 2015–2020, we find a median MAC of 429 €/t CO_2. Further, we find that the carbon intensity of revenue of the industry can be reduced by 3.96 to 10.61% if all firms would operate efficiently, depending on whether the median or mean inefficiencies were used for evaluation. Moreover, our findings indicate that the firm-level results vary widely, ranging from approximately 0 to 480 €/t CO_2. The range of estimated firm-level MACs fall within the range of abatement costs (which vary from −200 to 500 €/t CO_2) for the available carbon reduction technologies in the chemical industry. The variation in MACs among firms suggests that firms have access to different technological options to lower their carbon emissions. Firms with relatively low MACs have access to less expensive technologies, such as the electrification of process heat, solar process heat or CCS of process emissions. Conversely, the firms with higher MACs can only decrease their emissions by using more costly methods, such as using renewable hydrogen or bio-based organic materials as feedstock.

In line with other studies, we find that the empirical MACs exceed the relevant market price for carbon (Wei et al., 2013; Ma and Hailu, 2016; Ma et al., 2019; Ji and Zhou, 2020). As noted above, this is consistent with the use of the non-radial DFs, such as the DDF, and the fact that the carbon market price is determined by the supply and demand for allowances of all market players in the EU-ETS and our MAC is estimated for a limited sample. For most firms, the MAC is higher than an EU allowance price of 100 €/t CO_2, which indicates that these firms prefer to buy their emission allowances on secondary markets (or receive enough free allowances in primary allocations to cover their emissions), rather than to abate emissions within the firm. For some firms, the MAC is lower than an EU allowance price of 100 €/t CO_2. These firms may benefit from mitigating emissions within the firm and selling excess allowances on secondary markets. Further, consistent with previous studies, we find that the carbon intensity and market capitalization are negatively related to the MAC, pointing to economies of scale in abating carbon emissions (Wei et al., 2013; Wang et al., 2017; Jain and Kumar, 2018; Ji and Zhou, 2020).

Comparing our results with previous studies using the DDF method to derive the MAC is challenging, however. These previous studies refer to DMUs like provinces, cities, industries, or firms in various sectors of the economy other than the chemical sector (Matsushita and Yamane, 2012; Peng et al., 2012; Wei et al., 2013; Du et al., 2015; Xiao et al., 2017; Ma and Hailu, 2016; Wang et al., 2017; Jain and Kumar, 2018; Ji and Zhou, 2020). The difference in the economic interpretation of the MACs between these studies is mainly driven by the heterogeneity in the underlying characteristics of the studied DMUs (in particular, the carbon intensity may differ among DMUs), the functional form of the DDF, the directional vector that determines how the inputs and outputs are scaled to the production frontier, and other data characteristics.

As a caveat, it should be mentioned that our derived MACs and the economic interpretation thereof depend on the chosen estimation method, functional form, directional vector, and data inputs. For example, if the directional vector is assumed to be on a growth path favoring reducing the undesirable output relative to the desirable output (i.e., a carbon minimizing approach), the MAC of carbon emissions would be higher (Vardanyan and Noh, 2006; Ji and Zhou, 2020). We chose the production technology to be consistent with the current regulatory environment in which the European chemical sector operates, imposing relative carbon mitigation, while also assuming that firms follow the least-cost pathway to reduce their carbon intensities. It is also possible that the calculated MAC overestimates the actual abatement cost as new technologies are developed over time (Wei et al., 2013; Ma and Hailu, 2016). Further, we note that the chemical industry is a wide, complex and diverse industry associated with a broad range of products and technologies, different process routes for producing the same product, and firms producing products that belong to different subsectors, which makes it challenging to model the whole sector. However, as noted above, the group heterogeneity in our sample is consistent with the DDF, which assumes more extensive inter-factor substitutions of labor, capital and energy in long-run scenarios (Ma and Hailu, 2016). To account for the heterogeneity between firm technologies, the meta-frontier distance function may be a possible alternative (Zhang et al., 2013).

Overall, our findings indicate that the average MAC of the European chemical sector significantly exceeds the prevailing carbon market price. Consequently, we conclude that the industry lacks sufficient incentives to reduce its' own emissions, despite having the potential for emission abatement. This also implies that the industry will only be incentivized to adopt the more expensive abatement measures, such as chemical recycling or feedstock switching, when the carbon price is significantly higher or when financial support for these technologies is provided.

This research contains useful recommendations for policymakers. If policymakers find it desirable to achieve carbon emission reductions in the European chemical sector, they can provide the required incentives to chemical firms to realize this potential. For example, governments can subsidize the technological development or implementation of the more costly abatement technologies, as this may reduce the costs of these technologies significantly and, as a result, the chemical industry may choose to engage in abating actual emissions instead of buying allowances. Additionally, policymakers can use these results to identify the firms with a greater potential to abate emissions. In general, larger and more carbon-intensive firms are more likely to abate actual emissions using the lower-cost abatement technologies and, as a result, do not require subsidies for abatement. In contrast, smaller and relatively less-carbon intensive firms only have access to the more expensive abatement technologies, and may either purchase emission allowances to cover their emissions or require subsidies to achieve actual abatement. These findings may help governments to efficiently allocate subsidies and minimize the total abatement costs of reaching climate targets.

CRediT authorship contribution statement

Lennard Rekker: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation. **Machiel Mulder:** Conceptualization, Supervision. **Michaela Kesina:** Formal analysis, Supervision.

Appendix A

Table A.1
Information on included firms.

Company name	Ticker	ID	Subsector	Mean				
				Revenue (in billion EUR)	CO2 emissions (in thousands of tons)	Labor (in thousands of employees)	Capital (in billion EUR)	Energy consumption (in million MWh)
AIR LIQUIDE SA	AI FP Equity	1	Specialty chemicals	19.62	14,679.33	63.52	19.12	139.24
AKZO NOBEL N.V.	AKZA NA Equity	2	Specialty chemicals	10.16	65.58	37.97	2.63	1.71
ARKEMA	AKE FP Equity	3	Chemicals diversified	8.16	2828.00	19.80	2.72	8.14
BASF SE	BAS GR Equity	4	Chemicals diversified	61.32	17,295.67	115.35	23.19	56.10
BORREGAARD ASA	BRG NO Equity	5	Specialty chemicals	0.48	137.66	1.07	0.34	1.68
CLARIANT AG-REG	CLN SW Equity	6	Chemicals diversified	4.65	408.33	16.97	1.86	3.09
COVESTRO AG	1COV GR Equity	7	Specialty chemicals	12.64	1581.67	16.23	4.79	15.39
CRODA INTERNATIONAL PLC	CRDA LN Equity	8	Chemicals diversified	1.55	138.91	4.52	0.84	0.93
ELEMENTIS PLC	ELM LN Equity	9	Chemicals diversified	0.67	201.53	1.48	0.31	1.41
EVONIK INDUSTRIES AG	EVK GR Equity	10	Specialty chemicals	13.20	5332.80	34.34	6.58	22.33
GIVAUDAN-REG	GIVN SW Equity	11	Specialty chemicals	4.87	103.17	12.66	1.62	0.79
IMCD NV	IMCD NA Equity	12	Specialty chemicals	2.17	6.58	2.49	0.04	0.04
JOHNSON MATTHEY PLC	JMAT LN Equity	13	Chemicals diversified	14.51	206.76	12.88	1.51	1.40
K + S AG-REG	SDF GR Equity	14	Fertilizers	3.38	2100.00	14.71	6.04	11.81
KEMIRA OYJ	KEMIRA FH Equity	15	Chemicals diversified	2.48	152.00	4.86	0.98	4.39
LANXESS AG	LXS GR Equity	16	Chemicals diversified	6.98	1646.50	16.19	3.17	11.97
LENZING AG	LNZ AV Equity	17	Chemicals and Synthetic Fibers	2.05	1110.00	6.68	1.53	11.32
OCI NV	OCI NA Equity	18	Fertilizers	2.37	6810.00	3.08	5.08	65.94
SOLVAY SA	SOLB BB Equity	19	Chemicals diversified	10.77	10,390.00	25.78	5.89	40.79
SYMRISE AG	SY1 GR Equity	20	Chemicals diversified	3.10	205.93	9.48	0.99	1.43
SYNTHOMER PLC	SYNT LN Equity	21	Chemicals diversified	1.59	144.69	2.76	0.41	1.41
VICTREX PLC	VCT LN Equity	22	Specialty chemicals	0.34	22.26	0.85	0.30	0.17
WACKER CHEMIE AG	WCH GR Equity	23	Chemicals diversified	4.91	1334.75	15.25	3.61	13.08
YARA INTERNATIONAL ASA	YAR NO Equity	24	Fertilizers	10.84	15,016.67	15.46	6.91	77.08

Source: Bloomberg (2022).

Table A.2
Calculated parameters of the directional distance function.

Coefficient	Variable	Estimate
α_0	*intercept*	−1.588
α_1	x_1	1.145
α_2	x_2	−0.118
α_2	x_3	0.148
α_{11}	x_1^2	−0.452
α_{22}	x_2^2	−0.223
α_{33}	x_3^2	0.009
$\alpha_{12} = a_{21}$	x_1x_2	0.352
$\alpha_{12} = a_{21}$	x_1x_3	−0.133
$\alpha_{12} = a_{21}$	x_2x_3	0.051
β_1	y	−1.000
β_{11}	y^2	0.000
γ_1	b	0.176
γ_{11}	b^2	−0.034
δ_1	x_1y	0.000
δ_2	x_2y	0.000
δ_3	x_3y	0.000
η_1	x_1b	−0.010
η_2	x_2b	0.018
η_3	x_3b	−0.008
μ_{11}	by	0.000

Note: We do not report the parameter estimates of the year dummies (2016–2020) and firm dummies (2–24).

Table A.3
Estimated MAC (in €/t CO2) by firm.

Company name	Ticker	ID	Mean	Std. Dev.	Min.	Max.
AIR LIQUIDE SA	AI FP Equity	1	64.21	54.69	0.00	145.55
AKZO NOBEL N.V.	AKZA NA Equity	2	426.08	21.36	413.98	468.98
ARKEMA	AKE FP Equity	3	367.82	9.58	356.99	384.28
BASF SE	BAS GR Equity	4	92.18	88.74	0.00	236.71
BORREGAARD ASA	BRG NO Equity	5	434.29	1.31	433.15	436.88
CLARIANT AG-REG	CLN SW Equity	6	426.28	6.93	418.18	435.83
COVESTRO AG	1COV GR Equity	7	430.97	18.91	414.71	460.70
CRODA INTERNATIONAL PLC	CRDA LN Equity	8	436.02	2.56	433.83	440.79
ELEMENTIS PLC	ELM LN Equity	9	432.94	1.51	431.40	435.76
EVONIK INDUSTRIES AG	EVK GR Equity	10	311.32	20.71	290.50	344.44
GIVAUDAN-REG	GIVN SW Equity	11	437.22	4.06	432.47	442.36
IMCD NV	IMCD NA Equity	12	436.30	4.21	432.21	443.37
JOHNSON MATTHEY PLC	JMAT LN Equity	13	452.87	19.88	428.88	477.14
K + S AG-REG	SDF GR Equity	14	422.13	11.32	406.30	432.79
KEMIRA OYJ	KEMIRA FH Equity	15	433.22	1.67	431.14	435.80
LANXESS AG	LXS GR Equity	16	399.93	9.32	387.74	412.78
LENZING AG	LNZ AV Equity	17	407.82	8.37	400.76	423.76
OCI NV	OCI NA Equity	18	259.37	48.68	201.69	336.20
SOLVAY SA	SOLB BB Equity	19	179.16	16.76	164.38	208.96
SYMRISE AG	SY1 GR Equity	20	428.50	2.26	426.30	432.50
SYNTHOMER PLC	SYNT LN Equity	21	437.48	3.40	433.07	441.52
VICTREX PLC	VCT LN Equity	22	437.88	1.65	436.75	441.19
WACKER CHEMIE AG	WCH GR Equity	23	413.51	15.87	401.10	434.52
YARA INTERNATIONAL ASA	YAR NO Equity	24	66.67	42.72	22.52	130.56

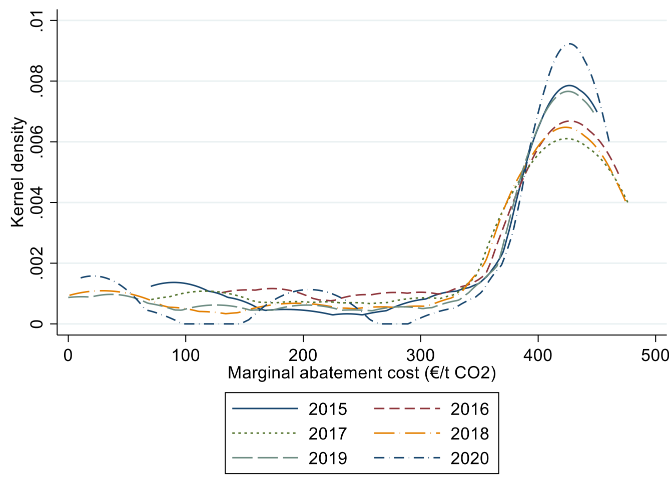

Fig. A.1. Kernel density curves of the MAC estimates for the years 2015 to 2020.

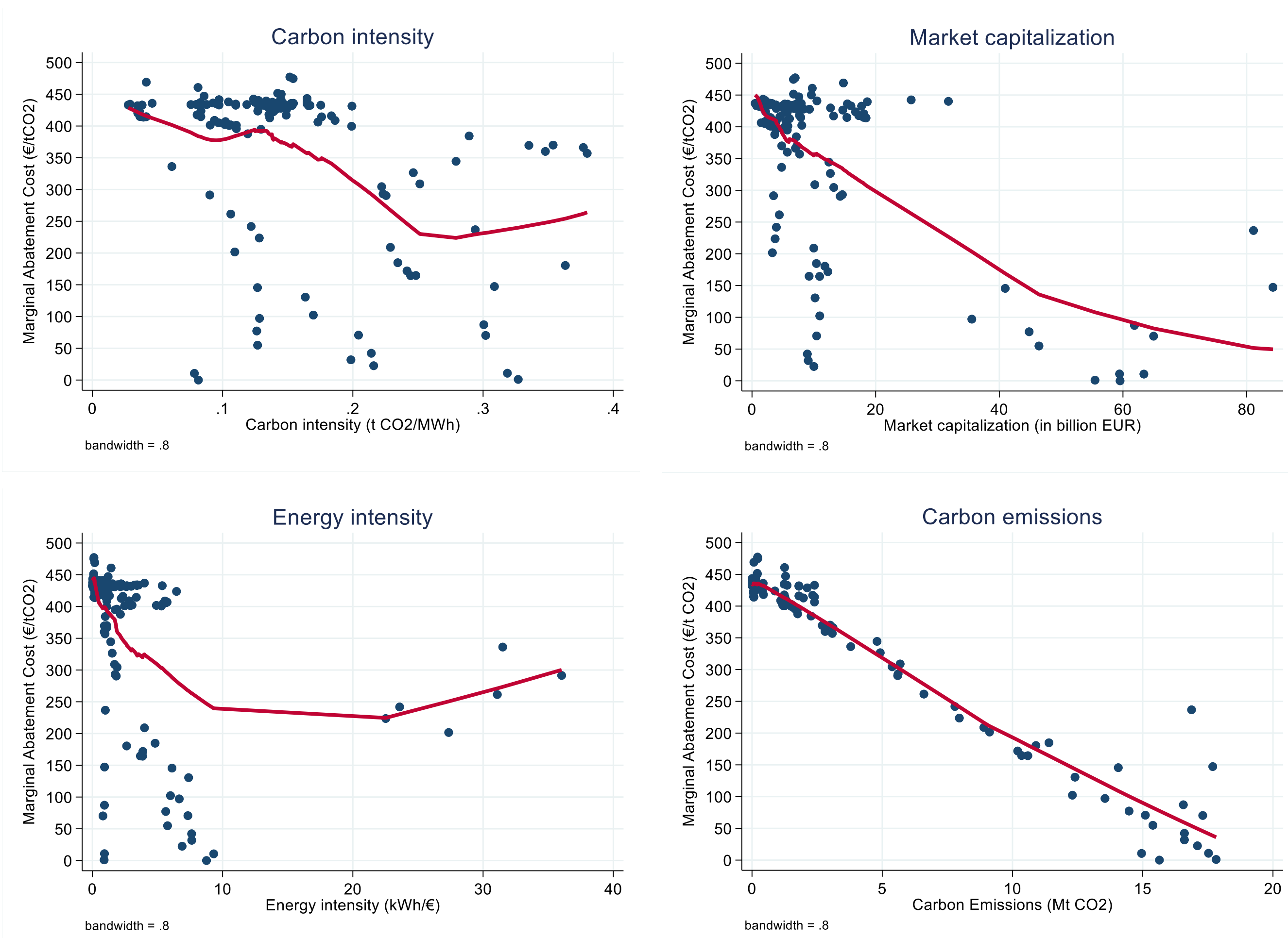

Fig. A.2. Locally Weighted Scatterplot Smoothing (LOWESS) of the estimated marginal abatement costs (in €/t CO_2) on carbon intensity (t CO_2/MWh), energy intensity (kWh/€), market capitalization (in billion EUR), and carbon emissions (in Mt. of CO_2) using the default brandwith of 0.8 and a tricube weight function.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2023.106889.

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