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Research Paper

Dissecting environmental efficiency: The role of technology adoption and usage

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ABSTRACT

How could firms best reduce their environmental impact? Should they change technology? Or could they do better with what they already have? This paper shows that one size does not fit all. We analyse a sample of polluting production plants (i.e. installations) regulated under the EU Emission Trading System. We employ a mixture model estimation to dissect environmental efficiency into a technology adoption component (*what* type of technology is used) and a technology usage component (*how* a technology is used). Our installation-level analysis shows that the share of installations adopting frontier technologies is about 21%. We also find that the average environmental efficiency gains that installations could reach by improving technology adoption and technology usage are 75% and 80% respectively. The analysis of balance-sheet data on parent companies reveals that better environmental technologies are adopted by larger, listed, multi-installation and international companies, while older firms and firms with higher intangible assets intensity more commonly show improved technology usage.

1. Introduction

Recent empirical evidence has documented that in many OECD countries emission intensity (measured as emissions per unit of output) of manufacturing sectors has been falling over the last decades (e.g., Najjar and Cherniwchan, 2021). Looking at the plant-level, the decline of emission intensity seems to be driven primarily by a within-product increase in environmental efficiency, i.e. an improvement in the ability to generate the same output at a lower environmental cost, rather than by changes in the composition of production (Shapiro and Walker, 2018). Yet, as it has been observed for standard economic measures of productivity (e.g., Hsieh and Klenow, 2009), environmental efficiency remains highly dispersed even within narrowly defined product-industries.

The sources of such heterogeneity are rather unexplored. In particular, it is still poorly understood whether within-product differentials in environmental efficiency are to be explained mainly in terms of differences in the type of technology adopted by different groups of firms (*what* type of technology is used) or as idiosyncratic differences across firms in the usage of technologies of a same type (*how* a technology is used). This paper aims at exploring this issue at the installation-level, i.e. at the level of each polluting production plant operating within narrowly defined product sectors. To what extent the within-product heterogeneity in environmental efficiency across installations is explained by differences in technology adoption, and to what extent by differences in technology usage? Measuring these dimensions has broad policy implications, as it would allow evaluating the potential gains in output, emissions being equal, of technology diffusion policies in comparison with policies aimed at improving technology usage.[1]

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[1] Technology diffusion policies cover a large array of measures, including both direct and indirect instruments, such as technology standards and adoption subsidies (Fisher and Newell, 2008; Acemoglu et al., 2012, 2016), whereas policies aimed at promoting technology usage are typically more nuanced and point to improving managerial and technical skills, environmental awareness, green accounting and, more in general, corporate social responsibility.

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A quantification of the gains from implementing such types of policies could help governments and regulatory agencies to better grasp the whole picture about green growth potentials besides those associated with more standard innovation policies alone.

The main reason of this lacuna is practical. On the one hand, measuring the technological component of environmental efficiency requires isolating each technology (or set of technologies that are equivalent in terms of emission intensity) available in a product-sector. Under standard techniques, this is possible only after conducting some form of ex-ante classification, e.g. based on an engineering approach with experts examining and classifying the technology in use firm-by-firm, to then estimate the emission coefficient (i.e. the additional emissions associated with an increase in output) for each type of technology. Such approaches are clearly unusable on a large scale. On the other hand, obtaining Solow residual-like measures of environmental efficiency at the firm (or installation) level under the assumption that a single emission coefficient can describe the production process in a sector implies imposing that all firms use technology of a same type, thereby confounding the firm-specific (technology usage) and the group-specific (technology adoption) dimensions of environmental efficiency.

In this paper we apply well-know statistical techniques in a new empirical context in order to decompose environmental efficiency into a group-level and an installation-level dimension.

We use data on installation-level pollution emissions and output obtained from the European Union's Operator Holding Accounts (EU OHA hereafter), which provide detailed information on verified CO_2 emissions and allocated emission permits for all European installations regulated under the EU Emission Trading System (EU ETS). Installations are identified as heavy energy-using power stations and other combustion plants with more than 20MW thermal rated input. In particular, we use permits data from the EU ETS Phase 3 (2013–2020) in order to recover, from the inverse permit allocation rule, physical output levels as the median activity level in 2005–2008 for each installation. We then match output levels with contemporaneous CO_2 emission levels obtained from the EU ETS Phase 1 (2005–2007). This allows us to afford additional granularity in the measurement of emission intensity relative to the existing literature and to capture cross-installation differences in technology adoption.

First, we employ an empirical mixture model to identify different "environmental-profile functions" (E-PFs) within narrowly defined industries, with each E-PF (identified by its constant and shape parameters) reflecting a type of production technology defined in terms of physical output generated per unit of emissions. In simple terms, the E-PF can be thought of as describing the polluting profile of the production process as determined by the characteristics of the technology in use. Our mixture model is similar in spirit to the one proposed by Battisti et al. (2015, 2020) in a more classical productivity context. It allows for the probability distribution of environmental efficiency to be the result of the potential overlapping of several distributions that we then interpret as different technology clusters, i.e. clusters of installations adopting production technologies with a same E-PF. The model leaves the estimation free to determine both the number of E-PFs available in each sector and the probability of each installation using each E-PF, including the one at the frontier (i.e. the technology profile associated with the minimum emission intensity).

Brought to the data, this exercise delivers a number of technology clusters ranging from one to five, with most sectors having more than one cluster. Our results square with the engineering of the actual production processes in the industries under analysis, as described by EPA (2022) among others, leading us to interpret the environmental profiles isolated in the model as arguably reflecting the environmental dimension of production technologies. For example, our model points to two relevant clusters in the production of carbon black, which are most likely to reflect the two main manufacturing processes actually used in the sector, i.e. the oil furnace process and the thermal process, which have different emission rates and require different emission control systems. In the lime and dolomite manufacturing, our model finds four clusters, consistently with the alternative use of rotary, shaft, calcimatic and fluidized bed kilns, which show very different fuel efficiencies. For the production of iron and steel, the two E-PFs identified in our model may capture the use of basic oxygen furnaces and electric arc furnaces in the steelmaking process, associated with different emission rates. Also for other sectors, we obtain a number of clusters that is in line with the actual technological differences between firms.

We then use the difference between the observed output of each installation and the estimated output associated with each E-PF to compute an installation-level measure of "environmental-profile usage" (E-PU), weighted by the installation's probability of adopting each available technology profile. The E-PU can be interpreted as the idiosyncratic component of the environmental performance of an installation, given the production technology. As a cross-installation differential, the E-PU captures the installation-specific ability to further mitigate the pollution generated in the production process with respect to the other installations adopting the same technology profile, e.g. by means of specific maintenance programs to make equipment work efficiently or using energy-saving internal logistics and materials management.[2]

In the sectors where more than one cluster is available, we find that the probability weighted share of installations adopting the frontier profile is about 21% and that the dispersion of the E-PU varies substantially depending on the technology in use (with E-PU variance being in most sectors lower for the installations in the frontier technology cluster).

In a second step, we quantify the potential gains in environmental efficiency from eliminating technology adoption and technology usage heterogeneity. We compute two counterfactual scenarios. One in which the installation adopts the frontier E-PF available in its sector and one in which the installation continues to be attached to the probability of adopting each profile as estimated in the first step but shows the E-PU of the top 5% performers in the sector. For each installation, we compare the output that would have been obtained under these two scenarios with the output actually observed. We find that adopting the frontier technology cluster would entail an average output gain at the installation-level by 75%, while improving technology usage

[2] Previous productivity research has shown that the Solow residual in standard production function estimation in part reflects managerial quality (e.g., Bhattacharya et al., 2013), which may be relevant also in our environmental context.

would increase output up to 80%, emissions being equal. On average, the total gain from technology upgrades when both sources of efficiency dispersion are eliminated is about 155%. These results are qualitatively similar when installation-level emissions are modelled as an endogenous variable and when emissions are expressed per unit of capital or unit of labour. Behind these averages, we also document that the growth margins of environmental efficiency differ substantially both across sectors and across installations within sectors, partly reflecting a number of characteristics of parent companies. We link each installation in the EU OHA database with its parent company in Orbis (Bureau van Dijk, 2022) by means of a fuzzy approach that matches account holder names in the EU OHA database and company names in Orbis. Consistently with previous literature on the competitive advantage of multinational companies (e.g., Forslid et al., 2018), we find that better technologies (in terms of output per unit of emissions) are more likely to be adopted by larger, listed, multi-installation and international companies, while older firms and firms with higher intangibles assets intensity more commonly show improved technology usage.

Taken together, our results suggest that existing technologies have large unexploited potentials, both because only a minor fraction of firms is adopting frontier technologies and because there is non-negligible room for improving the usage of currently adopted technologies. This points to the importance of coupling green innovation policies, aimed at promoting the development of new low-carbon technologies, with policies for broadening technology diffusion and good managerial and technical practices, in particular if emissions reduction goals are to be met in the short-run. Moreover, by unveiling significant cross-installation asymmetries in both technology adoption and usage, our statistical decomposition may lead to consider flexible environmental policies as an effective way for improving environmental efficiency—an insight in line with the "narrow" version of the so-called Porter Hypothesis which posits that flexible environmental regulations may give firms greater incentive to introduce technological innovations than prescriptive policy regimes (Jaffe and Palmer, 1997; Lanoie et al., 2011).

The paper proceeds as follows. In Section 2 we provide a brief overview of the related literature. In Section 3 we present the data. In Section 4 we explain in detail the steps of our methodology. In Section 5 we provide a quantification of the group-level and the installation-level components of environmental efficiency dispersion. In Section 6 we check the robustness of this quantification to different model specifications. Section 7 concludes by explaining the policy relevance of our analysis.

2. Related literature

The paper is at the intersection of two main literatures.

First is the literature on the diffusion of environmental technologies among regulated firms, i.e. technologies associated with a reduced environmental impact per unit of output, including technologies that reduce pollution at the end of the pipe, such as scrubbers for industrial smokestacks, and improved energy efficiency devices integrated into the production process. Popp et al. (2010) provide an extensive survey of this literature.[3] Recent research has focused on the question whether environmental regulations are responsible for the broader adoption of lower-emissions technologies observed in many countries and sectors. Shapiro and Walker (2018) find that changes in environmental regulations in the US account for most of the emissions reductions in US manufacturing between 1990 and 2008. Similarly, Najjar and Cherniwchan (2021) show that improved air quality standards in Canada caused reductions in the emission intensity of individual industries in Canadian manufacturing over the period 2004–2010. In the European context, Tchorzewska et al. (2022) show that the adoption of green technologies is encouraged by policy-mixes of environmental taxation and subsidies. With more specific reference to the European emission trading framework, Calel and Dechezlepretre (2016) find that the introduction of the EU ETS in 2005 has increased low-carbon innovation among companies included in the EU ETS, while Calel (2020) shows that the EU ETS has been effective in encouraging the production of low-carbon technologies without necessarily driving the diffusion of such technologies. This literature has improved our understanding of the shift in environmental technologies diffusion that can be attributed to changes in environmental regulations. However, it does not explore the technological differentials across firms regulated under the same regulatory framework. Moreover, by relying on data on low-carbon patenting, R&D spending or sector-specific technology classifications, most of this body of research tends to overlook cleaner technologies that are unpatented or difficult to classify in broad-scale analyses. Related to this, it is important to emphasize that patents and R&D spending are good proxies of innovation (i.e. the production of new technologies), but they may fail to capture technology adoption. While the use of some environmental technologies may be linked to a complementary innovation (thereby being associated to patent applications and R&D activities), many others may be introduced in the production process as such, without implying additional R&D investments.[4] The methodology proposed in the present paper allows to address this gap.[5]

Second, and to a lower extent, our paper may also be linked to the literature on the environmental consequences of managerial quality. Our measure of technology usage could be interpreted as reflecting environmental practices at the installation level, net of the technological dimension. Hence, our results on technology usage may speak to previous research discussing the relationship between firm management and environmental performance. For example, it has been argued that the adoption of pollution-reducing technologies may be prevented by organizational failures and managerial inertia (Porter and van der Linde, 1995; Ambec and Barla, 2002). Bloom et al. (2010) show that better managed establishments are significantly less energy intensive in a sample of 300 manufacturing firms in the UK. Martin et al. (2012) interviewed managers of 190 manufacturing plants in the UK and find that

[3] Allan et al. (2014) clarify the position of the literature on diffusion of environmentally beneficial technologies into the general topic of technology diffusion.

[4] As an example, the substitution of a basic oxygen furnace with an electric arc furnace in a steelmaking plant does not require particular R&D investments, but the two types of furnace are associated to different CO_2 emission rates.

[5] Our methodology may also contribute to the broader literature on the measurement of firm-level upgrading and technology adoption outside the environmental context (see Verhoogen, 2023 for an overview).

climate friendly management practices are associated with lower energy intensity and higher productivity. De Haas et al. (2021) show that managerial constraints slow down firm investment in more energy efficient and less polluting technologies, using data for a large sample of firms in 22 emerging markets. Gaganis et al. (2023) find that firms with more able managers have lower greenhouse gas emissions, in a cross-country sample of 407 publicly listed firms. Chen et al. (2021) point to the human capital of the workers more in general as a driver of better compliance with environmental regulations and reduced firm emissions.

3. Data

Before explaining the details of our empirical strategy, here we present the data. We use installation-level data provided by the EU OHA, which is carried out by the European Commission and covers all the installations regulated under the EU ETS.[6] The database provides accurate information on tons of verified CO_2-equivalent emissions and the number of allocated emission permits for each installation and year covered by the EU ETS, along with information on the installation's location and product-sector.[7]

We are able to retrieve installation-level output from the allowance allocation rule employed in the EU ETS Phase 3 (2013–2020). Over the years 2013–2020, allocation of allowances was administrated by the following rule:

$$A_{i,t,s} = \tilde{e}_s \ \lambda_{s,t} \ \vartheta_t \ Q_{i,s}, \tag{1}$$

where $A_{i,t,s}$ is the allowances to installation i in year t and sector s, $\tilde{e}_s$ is the sectoral benchmark emission intensity, $\lambda_{s,t}$ is a carbon leakage exposure factor (CLEF), ϑ_t is a cross-sectoral correction factor (CSCF) and $Q_{i,s}$ is the baseline activity level calculated as the median of the activity level in 2005–2008. Since $A_{i,t,s}$, $\tilde{e}_s$, $\lambda_{s,t}$ and ϑ_t are known, $Q_{i,s}$ can be retrieved by manipulating Eq. (1).[8] Installation-level annual tons of verified CO_2-equivalent emissions ($E_{i,t,s}$) are directly obtained from the EU OHA. In order to match physical output levels with contemporaneous emission levels, we use the median value of emissions over the EU ETS Phase 1 (denoted hereafter with $E_{i,s}$, for simplicity). Hence, an installation's emission intensity can be calculated as:

$$e_{i,s} = \frac{E_{i,s}}{Q_{i,s}}. \tag{2}$$

Environmental efficiency is nothing else than the reciprocal of $e_{i,s}$. Since our empirical analysis is conducted sector-by-sector, under a narrow product-sector classification, possible differences in the unit of measurement of $Q_{i,s}$ across sectors are not an issue.[9] However, we cannot exclude measurement errors stemming from a misalignment between the median values of emissions and outputs in the years of the EU ETS Phase 1. It is also possible that measuring $E_{i,s}$ with other pollutants different from CO_2-equivalent emissions would lead to non-negligible changes in the distribution of $e_{i,s}$ with respect to the one documented in this paper. In any case, it is impossible to predict in which direction measurement errors may drive our final results. There is no reason to expect misaligned median values of emissions and outputs to be systematically asymmetric towards one rather than the other side (thereby causing an under- or an over-bias in our emission intensity measure). In our mixture model analysis presented below, if measurement errors occur at random, they do not alter the distribution of $e_{i,s}$ and therefore do not imply distortions in the results.

Given our strategy to recover $Q_{i,s}$ and $E_{i,s}$, we restrict our sample to those installations that were active both in the EU ETS Phase 1 and Phase 3, which means about 75.9% of all the installations active during Phase 1. After data cleaning, we remain with 1881 installation-level observations over 14 product-sectors and 15 countries. Fig. 1 describes the cross-sector and cross-country composition of our final sample.

The cross-sectional distribution of e_i within each industry is illustrated in Fig. 2. As the figure shows, there are significant emission intensity differentials across installations. The sense of scale of these differentials can be grasped by considering that, in most of the sectors, the emission intensity of the installation at the 75th percentile of the distribution is about as twice as the emission intensity of the installation at the 25th percentile.

While this evidence suggests that dispersion of environmental efficiency is significant even in narrowly defined industries, it reveals little as to whether this heterogeneity is driven by installation-level or group-level sources. This is explored next.

[6] The system includes more than 11 000 installations operating in energy activities (combustion installations, mineral oil refineries, coke ovens), mineral industry (cement clinker, glass and ceramic bricks), production and processing of ferrous metals and pulp, paper and board activities, that each year receive (or must buy) a certain amount of allowances to emit greenhouse gases.

[7] The standard methodology to calculate CO_2 emissions, as then reported in the EU OHA, is based on multiplying the amount of fuel or other material combusted with corresponding emission factors. Variants of the standard methodology are used in some sectors (details are provided in European Commission (2018)).

[8] The CLEF is constant 1 or decreasing at a predetermined rate depending on the carbon leakage status of the sector, while the CSCF is a time-varying factor (constant across sectors) ensuring that total allocation remains below the maximum amount pursuant to article 10a(5) of the EU ETS Directive (European Commission, 2015). Product-specific benchmark emission intensities are listed in European Commission (2011) according to a classification that is more granular than the EU OHA sectors classification. We cross-walked the two classifications using product-sector description matching. Unmatched sectors are left out of the analysis. Details on CLEF, CSCF and benchmark emission intensities are provided in Appendix.

[9] By using a narrow product-sector classification at the installation level, we minimize the risk of confounding cross-installation variation within products with cross-product variation within firms (i.e. the "product-mix" effect, which is found to explain emission intensity dispersion about half as much as the variation across firms; see, e.g. Barrows and Ollivier, 2018). In any event, it is worth noting that our industry classification is more granular than commonly used classifications in related productivity literature (e.g., Battisti et al., 2020).

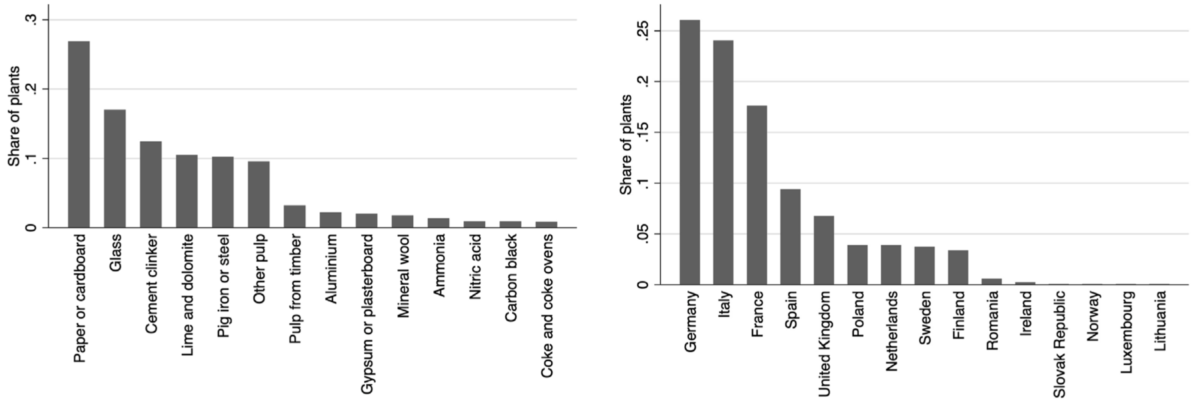

Fig. 1. Sample composition across sectors and countries. Note. Share of installations across sectors and countries.

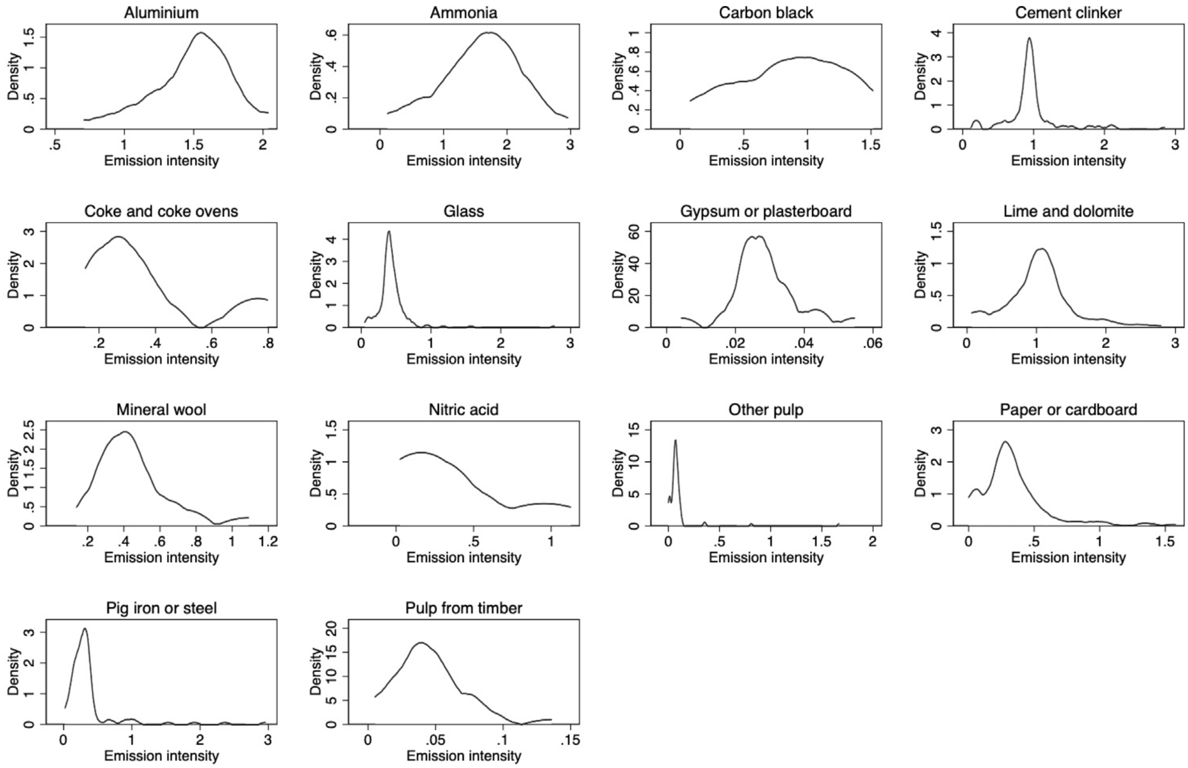

Fig. 2. Distribution of emission intensity within sectors. Note. Emission intensity is measured at the installation-level as verified tons of CO_2-equivalent emissions per unit of output. The default unit of measurement of output is tons of product produced expressed as saleable net production and to 100% purity of the substance concerned (details are in European Commission, 2011).

4. Measuring technology adoption and usage

With our analysis we want to dissect environmental efficiency of installations in two components, reflecting respectively the extent to which environmental efficiency is due to the type of technology employed in production (a technology-type is assumed to be common to more than one installation, hence it is a group-level dimension) and the extent to which it is due to factors associated with the idiosyncratic (installation-level) usage of the technology. To achieve this decomposition we proceed in two steps. First, we need to cluster installations depending on the technology in use, where each cluster brings together all the installations adopting a same technology or different technologies of a same type in terms of output-to-emission ratios (i.e. technologies that are environmentally equivalent). Second, we measure the idiosyncratic component as the difference between the observed installation-level environmental efficiency and the predicted environmental efficiency within the same technology cluster.

We begin by formalizing the association between output and emissions of installation i in sector s as follows:

$$Q_i = \Psi_{i,\tau} E_i^{\beta_\tau}, \tag{3}$$

where $\Psi_{i,\tau}$ is the environmental efficiency of installation i when it uses the technology-type τ among the $\mathcal{T}$ technology-types available in the sector.

Taking natural logs of Eq. (3) results in

$$\ln(Q_i) = \alpha_{i,\tau} + \alpha_\tau + \beta_\tau \ln(E_i), \tag{4}$$

with $\ln(\Psi_{i,\tau}) = \alpha_{i,\tau} + \alpha_\tau$. The parameters α_τ and β_τ are the constant and shape coefficients of the τ-technology-type. Hence, $\{\alpha_\tau, \beta_\tau\}$ describes the "environmental-profile function" (E-PF), i.e. the function generating the predicted output per unit of emissions from using a technology of type τ. It is clear that, in this framework, two (or more) technologies are considered of a same type (which equals to say that they can be described by a same E-PF) even if they employ different amounts of capital and labour inputs, or a different mix of them, provided that such technologies have a same profile in terms of output-to-emission ratios. In more explicit terms, we consider a technology-type as broader than a unique combination of physical inputs: if two installations use different amounts of capital with a different intensity, labour being equal, generating the same amounts of output and emissions, then they are considered as employing environmentally equivalent technologies and are associated to the same technology cluster τ. From this, it also follows that, in our framework, a firm exposed to a demand-side shock, pushing down production levels, remains correctly associated to the same technology it was using before the shock, to the extent that the firm's output-to-emission ratio remains constant.

In Eq. (4), the residual term $\alpha_{i,\tau}$ reflects the idiosyncratic deviation of installation i's output with respect to the fitted output of the installations adopting the same technology-type τ. We refer to $\alpha_{i,\tau}$ as the "environmental-profile usage" (E-PU), which, net of the technological dimension, can be thought of as representing the installation-specific idiosyncratic component of environmental efficiency.[10] By measuring output in physical quantities instead of value added or revenues, we avoid the omitted price bias of the type discussed by previous literature (e.g., Klette and Griliches, 1996).

We obtain α_τ and β_τ by estimating Eq. (4) with a finite mixture model (McLachlan et al., 2019) on our installation-level data sector-by-sector. Under such type of modelling, the within-sector distribution of $\ln(Q_i)$ is the average of $\mathcal{T}$ Gaussian distributions, each with own mean μ_τ and variance σ_τ^2, weighted by the ex-ante probabilities π_τ of belonging to group τ, i.e.:

$$f\left(\ln(Q_i)|\mu, \sigma^2\right) = \sum_{\tau=1}^{\mathcal{T}} \pi_\tau f_\tau \left(\ln(Q_i)|\mu_\tau, \sigma_\tau^2\right), \tag{5}$$

where

$$\pi_\tau = \frac{\sum_{i=1}^{N} p_{i,\tau}}{\sum_{\tau=1}^{\mathcal{T}} \sum_{i=1}^{N} p_{i,\tau}}, \tag{6}$$

with N being the number of installations and $p_{i,\tau}$ the posterior probabilities. It is imposed that $\sum_{\tau=1}^{\mathcal{T}} \pi_\tau = 1$.

Posterior probabilities $p_{i,\tau}$ are obtained by using an expectation–maximization (EM) algorithm to the sector-by-sector weighted least squares estimation of Eq. (4). In the expectation (E) step, posterior probabilities $p_{i,\tau}$ are computed as

$$p_{i,\tau} = \frac{\pi_\tau f_\tau \{\ln(Q_i)|\mu_\tau; \sigma_\tau^2\}}{\sum_{\tau=1}^{\mathcal{T}} \pi_\tau f_\tau \{\ln(Q_i)|\mu_\tau; \sigma_\tau^2\}}, \tag{7}$$

starting from random values of π_τ. In the maximization (M) step, the likelihood for Eq. (4) is maximized using observation weights:

$$\gamma_{i,\tau} = \sqrt{p_{i,\tau}}. \tag{8}$$

The two steps are iterated until the likelihood converges. We denote with $\tilde{p}_{i,\tau}$ the posterior probabilities obtained after the last EM iteration, once the likelihood is converged.[11]

We leave the model free to choose, in each sector, the number of technology clusters that best fits the data. We do so by running the mixture model estimation of Eq. (4) repeatedly, imposing in each round a different number of clusters $\mathcal{T} \in [1, 10]$ and selecting the number of clusters that minimizes the Bayesian information criterion (BIC).[12] We denote with $\tilde{\mathcal{T}}$ such optimal number. Detailed results of our BIC-based selection procedure are collected in Table 1. Our mixture model estimation delivers a number of clusters ranging from one to five, with most sectors having more than one cluster.

[10] Note that $\alpha_{i,\tau}$ captures the idiosyncratic component of environmental efficiency only if capital, labour and intermediate inputs are not included in Eq. (3). If marketed inputs were added into Eq. (3), a variation in one of these inputs, output and emissions being equal, would reflect in some variation in $\alpha_{i,\tau}$ without the actual idiosyncratic deviation in environmental efficiency of installation i being changed.

[11] It is evident that our empirical strategy is different and computationally less intensive than environmental efficiency techniques based on environmental production function models and data envelopment analysis (e.g., Färe et al., 2005), stochastic frontier models (e.g., Fernández et al., 2002), hyperbolic output efficiency measurement (e.g., Färe et al., 1989) and directional distance function approaches (e.g., Chung et al., 1997), which boil together desirable and undesirable outputs and inputs, without disentangling technical efficiency (productivity) from environmental efficiency, and cannot separate the between-technology and within-technology components that are crucial in our framework.

[12] A number of $\mathcal{T}$ higher than 10 could be considered, but we observed empirically that in our data the model does not converge for $\mathcal{T} > 5$ in any sector.

Table 1
BIC values from the sector-by-sector mixture model estimation.

Sector	$BIC_{\mathcal{T}=1}$	$BIC_{\mathcal{T}=2}$	$BIC_{\mathcal{T}=3}$	$BIC_{\mathcal{T}=4}$	$BIC_{\mathcal{T}=5}$	$BIC_{\mathcal{T}=6}$	$BIC_{\mathcal{T}=7}$	$BIC_{\mathcal{T}=8}$	$BIC_{\mathcal{T}=9}$	$BIC_{\mathcal{T}=10}$	BIC_{min}	$\tilde{\mathcal{T}}$
Aluminium	55.476	78.963	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	55.476	1
Ammonia	11.373	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	11.373	1
Carbon black	11.953	6.694	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	6.694	2
Cement clinker	199.759	51.661	43.964	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	43.964	3
Coke and coke ovens	19.193	25.188	21.160	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	19.193	1
Glass	279.792	182.605	174.329	163.654	145.700	n.c.	n.c.	n.c.	n.c.	n.c.	145.700	5
Gypsum or plasterboard	16.323	13.717	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	16.323	2
Lime and dolomite	283.474	204.808	212.997	189.685	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	189.685	4
Mineral wool	32.714	37.133	30.905	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	30.905	3
Nitric acid	40.613	17.581	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	17.581	2
Other pulp	293.492	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	293.492	1
Paper or cardboard	894.623	631.598	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	631.598	2
Pig iron or steel	315.812	271.033	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	271.033	2
Pulp from timber	86.536	83.353	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	83.353	2

Note. $\mathcal{T}$= number of technology clusters (i.e. number of E-PFs), $\tilde{\mathcal{T}} = \mathcal{T}$ corresponding to BIC_{min}, n.c. = not converged.

Table 2
E-PF parameters from the sector-by-sector mixture model estimation.

Sector	$E\text{-}PF_1$	$E\text{-}PF_2$	$E\text{-}PF_3$	$E\text{-}PF_4$	$E\text{-}PF_5$
Aluminium	$\beta_1 = 0.944$ $\alpha_1 = 0.000$				
Ammonia	$\beta_1 = 0.151$ $\alpha_1 = 0.000$				
Carbon black	$\beta_1 = 0.250$ $\alpha_1 = 8.407$	$\beta_2 = 0.793$ $\alpha_2 = 0.000$			
Cement clinker	$\beta_1 = 0.974$ $\alpha_1 = 0.284$	$\beta_2 = 0.419$ $\alpha_2 = 7.956$	$\beta_3 = 0.975$ $\alpha_3 = 0.384$		
Coke and coke ovens	$\beta_1 = 0.852$ $\alpha_1 = 3.020$				
Glass	$\beta_1 = 0.973$ $\alpha_1 = 1.141$	$\beta_2 = 0.980$ $\alpha_2 = 0.358$	$\beta_3 = 0.208$ $\alpha_3 = 9.760$	$\beta_4 = 0.561$ $\alpha_4 = 5.748$	$\beta_5 = 0.766$ $\alpha_4 = 3.424$
Gypsum or plasterboard	$\beta_1 = 0.264$ $\alpha_1 = 10.819$	$\beta_2 = 0.864$ $\alpha_2 = 0.000$			
Lime and dolomite	$\beta_1 = 1.170$ $\alpha_1 = -2.620$	$\beta_2 = 0.367$ $\alpha_2 = 0.003$	$\beta_3 = 0.373$ $\alpha_3 = 0.082$	$\beta_4 = 1.069$ $\alpha_4 = 0.048$	
Mineral wool	$\beta_1 = 0.811$ $\alpha_1 = 2.066$	$\beta_2 = 0.658$ $\alpha_2 = 0.000$	$\beta_3 = 1.057$ $\alpha_3 = 0.272$		
Nitric acid	$\beta_1 = 1.306$ $\alpha_1 = -2.485$	$\beta_2 = 0.602$ $\alpha_2 = 0.000$			
Other pulp	$\beta_1 = 0.359$ $\alpha_1 = 9.203$				
Paper or cardboard	$\beta_1 = 0.857$ $\alpha_1 = 2.542$	$\beta_2 = 0.065$ $\alpha_2 = 12.441$			
Pig iron or steel	$\beta_1 = 0.860$ $\alpha_1 = 2.877$	$\beta_2 = 1.004$ $\alpha_2 = 1.236$			
Pulp from timber	$\beta_1 = 0.856$ $\alpha_1 = 4.548$	$\beta_2 = 0.590$ $\alpha_2 = 0.000$			

Note. All the reported parameters are statistically significant at the 1% level. Both α and β are considered equal to zero if not statistically different from zero at the 1% level.

As a simple external validity check of these results, for each sector we compare the number of technology clusters identified by our model with a standard classification of the actual production processes provided by EPA (2022). In the Appendix, we provide a summary of the relevant technical aspects. Reassuringly, our clustering squares with the main differences across the technologies typically used by actual installations.

Table 2 reports the estimated α_τ and β_τ coefficients for the $\tilde{\mathcal{T}}$ technology clusters identified in each sector. While the emission coefficient β_τ is generally lower than one, a few clusters have β_τ greater than one. All the E-PFs are plotted in Fig. 3.

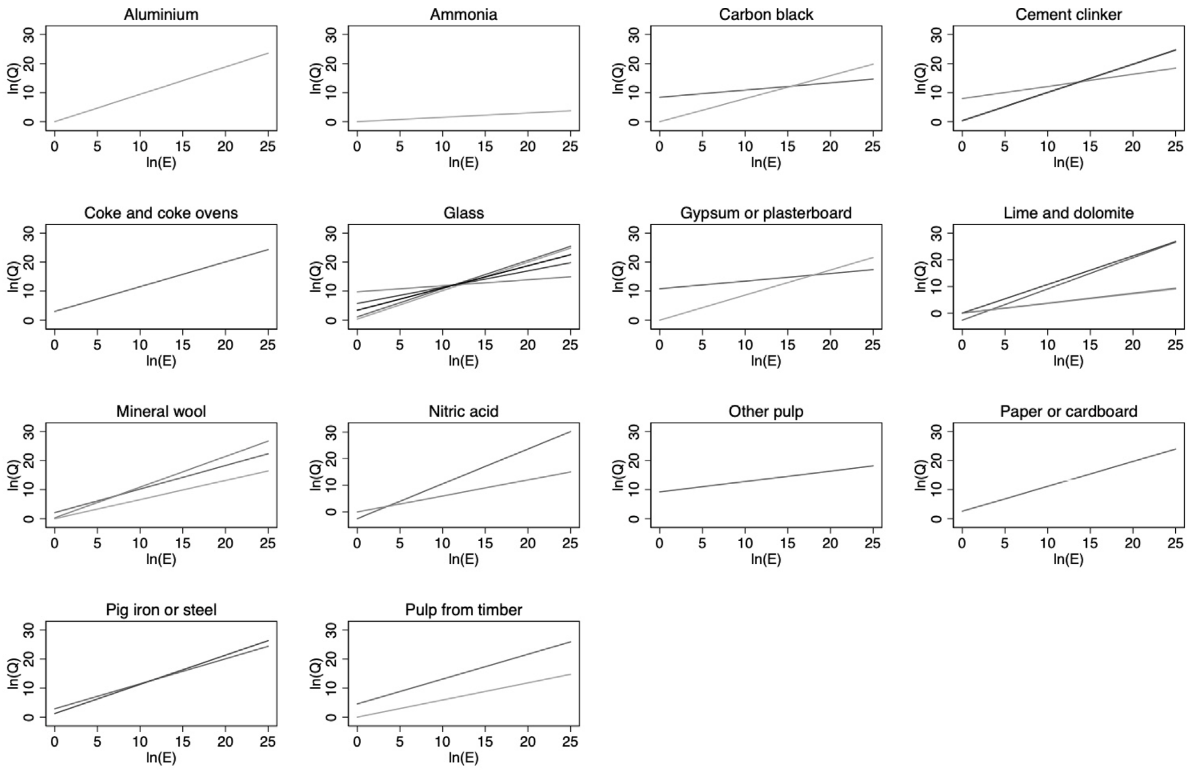

Fig. 3. Estimated E-PFs. Note. E-PFs obtained from the mixture model estimation. The number of E-PFs in each sector is determined as the result of optimal clustering selection based on BIC minimization.

Once the parameters describing each E-PF are obtained, we are able to identify the locally optimal technology-type τ^*, referred to as the technology-type such that $\ln(\hat{Q}_{i,\tau^*})|E_i > \ln(\hat{Q}_{i,\tau})|E_i \quad \forall \tau \neq \tau^*$.[13] Note that τ^* is "locally" optimal because conditional on E_i, i.e. two or more E-PFs may cross each other at some level of E_i. Indeed, as shown in Fig. 3, in most sectors, we observe that there is not a unique optimal technology-type for any level of E_i. This means that the relative performance of environmental technologies is emission-contingent, with the technologies which perform relatively well at low levels of emissions tending to perform worse in highly polluting (and arguably larger) installations.[14]

For each installation we have the probability $\tilde{p}_{i,\tau}$ of adopting each cluster τ as well as the probability $\tilde{p}_{i,\tau^*}$ of adopting the locally optimal technology-type τ^*. Hence, we can calculate the probability-weighted size of each technology cluster, including the one that is locally optimal. We observe that the cross-cluster distribution of installations vary considerably both within and across sectors. In particular, in the sectors where $\tilde{\mathcal{T}} \geq 2$, the within-sector share of installations adopting the technology-type τ^* ranges from 6.10% in the production of lime and dolomite to 54.25% in the carbon black industry, it being 21.12% on average. When installations from all sectors are pooled, the share of installations at the technological frontier is 31.85%. The full distributions of installations across technology clusters and sectors are provided in Table 3. This result unveils that the accessibility of the frontier technologies may differ remarkably across industries, with most installations in most sectors using sub-optimal technologies.

Finally, we obtain the E-PU term $\alpha_{i,\tau}$ as the difference between the installation's observed output and the fitted output under each E-PF (weighted by the probability of adopting each E-PF), i.e. as

$$\ln(Q_i) - \sum_{\tau=1}^{\tilde{\mathcal{T}}} \tilde{p}_{i,\tau} \ln(\hat{Q}_{i,\tau}), \tag{9}$$

with $\ln(\hat{Q}_{i,\tau}) = \alpha_\tau + \beta_\tau \ln(E_i)$.

[13] Clearly, this notion of optimality refers to the environmental performance of the technology (in terms of emission intensity minimization). An optimal environmental technology-type may be in fact sub-optimal from a profit-maximization perspective.

[14] Note that, for high levels of output and emissions (i.e. above and to the right of the point where the E-PFs intersect each other), the E-PF with the highest β coefficient is by construction the one describing the technology-type associated with the highest environmental efficiency. As the levels of emissions and output are normally associated with the size of installations, this equals to say that the aggregate Q-to-E ratio is higher when installations have a relatively large scale (i.e. they are above and to the right of the kink point—or of the "last" kink point if there are multiple kinks) and at the same time adopt the technology-type with the highest shape parameter.

Table 3
Probability-weighted distributions of installations across clusters and sectors (%).

Sector	$\tau = \tau_1$	$\tau = \tau_2$	$\tau = \tau_3$	$\tau = \tau_4$	$\tau = \tau_5$	$\tau = \tau^*$
Aluminium	100					100
Ammonia	100					100
Carbon black	74.04	25.95				54.25
Cement clinker	35.58	7.05	57.35			18.31
Coke and coke ovens	100					100
Glass	60.958	7.61	3.42	22.20	5.79	19.88
Gypsum or plasterboard	56.44	43.55				51.42
Lime and dolomite	6.79	24.27	4.55	64.37		6.10
Mineral wool	16.79	25.51	57.69			27.07
Nitric acid	54.48	45.50				41.98
Other pulp	100					100
Paper or cardboard	86.36	13.63				14.53
Pig iron or steel	33.29	66.70				41.26
Pulp from timber	60.88	39.11				37.89
All sectors pooled						31.85
All sectors with $\tilde{\mathcal{T}} \geq 2$ pooled						21.12

Note. Entries are within-sector shares (%) of observations across technology clusters, weighted by the probability $\tilde{p}_{i,\tau}$ of belonging to each cluster. The locally optimal technology cluster is τ^*.

Table 4
E-PU dispersion conditional on technology-type.

Sector	$\widehat{\mathrm{Var}}(\alpha_{i,\tau^*})$	$\widehat{\mathrm{Var}}(\alpha_{i,\tau\neq\tau^*})$
Aluminium	0.063	–
Ammonia	0.122	–
Carbon black	0.026	0.017
Cement clinker	0.003	0.057
Coke and coke ovens	0.222	–
Glass	0.002	0.020
Gypsum or plasterboard	0.002	0.010
Lime and dolomite	0.001	0.043
Mineral wool	0.004	0.015
Nitric acid	0.050	0.084
Other pulp	0.846	–
Paper or cardboard	0.052	0.193
Pig iron or steel	0.315	0.200
Pulp from timber	0.158	0.436

Note. $\widehat{\mathrm{Var}}(\alpha_{i,\tau\neq\tau^*}) = -$ in sectors where $\tilde{\mathcal{T}} = 1$.

To understand how the dispersion of the E-PU varies conditional on the technology-type in use at the installation level, we compute two additional versions of $\alpha_{i,\tau}$, conditional respectively on the locally optimal and sub-optimal technology clusters, i.e.

$$\alpha_{i,\tau^*} = \ln(Q_i) - \tilde{p}_{i,\tau^*} \ln(\hat{Q}_{i,\tau^*}) \qquad \text{and} \qquad \alpha_{i,\tau\neq\tau^*} = \ln(Q_i) - \sum_{\tau\neq\tau^*} \tilde{p}_{i,\tau} \ln(\hat{Q}_{i,\tau}), \tag{10}$$

and compare their estimated variances. Sectoral figures are in Table 4. We find that $\widehat{\mathrm{Var}}(\alpha_{i,\tau^*}) > \widehat{\mathrm{Var}}(\alpha_{i,\tau\neq\tau^*})$ only in the production of carbon black and pig iron, while the opposite holds in all the other sectors with $\tilde{\mathcal{T}} \geq 2$, thereby revealing that the adoption of the frontier technology-type may help to reduce cross-installation differentials in technology usage performance. This finding may be interesting in light of very recent research showing that environmental management quality correlates positively with green investments at the firm level (De Haas et al., 2021).

5. Green growth potentials

Once the technology adoption and the technology usage dimensions of environmental efficiency are identified, a natural question is whether their economic significance is relevant. In this Section, we address this point by quantifying the potential gains in output that could be obtained by improving on both dimensions without additional environmental costs (in terms of CO_2-equivalent emissions).

First, we measure an E-PF $gain_i$ index, obtained as the difference between the output associated with the best available technology-type in the sector and the weighted fitted output associated with the type of technology actually in use by the individual installation. Formally:

$$\text{E-PF } gain_i = \ln(\hat{Q}_{i,\tau^*}) - \sum_{\tau=1}^{\tilde{\mathcal{T}}} \tilde{p}_{i,\tau} \ln(\hat{Q}_{i,\tau}), \tag{11}$$

Table 5
Potential gains from eliminating emission intensity dispersion.

Sector	E-PF $gain_i$	E-PU $gain_i$	$Total\ gain_i$
Aluminium	0.000	0.595	0.595
	(0.000)	(0.219)	(0.219)
Ammonia	0.000	0.429	0.429
	(0.000)	(0.349)	(0.349)
Carbon black	0.102	0.386	0.488
	(0.148)	(0.211)	(0.267)
Cement clinker	0.478	0.578	1.057
	(0.612)	(0.249)	(0.666)
Coke and coke ovens	0.000	0.571	0.571
	(0.000)	(0.471)	(0.471)
Glass	0.534	0.332	0.867
	(0.589)	(0.154)	(0.608)
Gypsum or plasterboard	0.122	0.169	0.292
	(0.169)	(0.113)	(0.217)
Lime and dolomite	1.037	0.452	1.489
	(0.928)	(0.210)	(0.997)
Mineral wool	0.521	0.267	0.788
	(0.534)	(0.132)	(0.568)
Nitric acid	1.159	0.571	1.730
	(1.420)	(0.347)	(1.484)
Other pulp	0.000	1.692	1.692
	(0.000)	(0.834)	(0.834)
Paper or cardboard	1.754	0.883	2.637
	(1.153)	(0.481)	(1.194)
Pig iron or steel	0.102	1.259	1.362
	(0.125)	(0.638)	(0.664)
Pulp from timber	0.136	1.710	1.847
	(0.203)	(0.723)	(0.810)
All sectors pooled	0.755	0.800	1.555
	(0.999)	(0.640)	(1.128)

Note. E-PF $gain_i$ quantifies the increase in Q that would be obtained by moving to the counterfactual scenario where all firms adopt E-PF*, expressed as a ratio with respect to the observed (i.e. actual) levels of Q. E-PU $gain_i$ quantifies the increase in Q that would be obtained by moving to the counterfactual scenario where all firms have E-PU*, the technology in use being equal, expressed as a ratio with respect to the observed (i.e. actual) levels of Q. $Total\ gain_i$ is the sum of E-PF $gain_i$ plus E-PU $gain_i$. E-PF $gain_i$, E-PU $gain_i$ and $Total\ gain_i$ are calculated at the installation-level and then reported in the table as sector-averages. Standard deviation in parenthesis.

In simple words, E-PF $gain_i$ measures the increase in output that would be associated with a switch to the technological frontier, the installation's E-PU being zero.

Second, we compute an index of the output gain that an installation could obtain by adopting the best usage practices available in the sector, the technology in use being the same. We refer to this index as E-PU $gain_i$ and obtain it as the difference between the E-PU of the top 5% performers in the sector and the E-PU of the individual installation. More formally:

$$\text{E-PU } gain_i = \alpha^* - \alpha_{i,\tau} \tag{12}$$

where $\alpha_{i,\tau}$ is defined as in (9) and α^* is the average $\alpha_{i,\tau}$ of the best 5% of installations in the within-sector distribution of $\alpha_{i,\tau}$.[15]

As a difference between logarithmic terms, both E-PF $gain_i$ and E-PU $gain_i$ can be directly interpreted as output gains in percentage points. By construction, the sum of E-PF $gain_i$ plus E-PU $gain_i$ is the total environmental efficiency distance from the "frontier installation", referred to as the installation in the top 5% performers in terms of E-PU that adopts the locally optimal technology-type. Denote the sum E-PF $gain_i$ + E-PU $gain_i$ with $Total\ gain_i$. Clearly, these potential gains are to be interpreted as upper bounds, as moving to the frontier may be unfeasible in reality for many installations.

Table 5 reports the sectoral averages of E-PF $gain_i$, E-PU $gain_i$ and $Total\ gain_i$.[16]

Two main results emerge. On the one side, both the group-level and the installation-level dimensions are associated with economically significant environmental efficiency dispersion. In particular, switching to the frontier technology cluster would increase average output at the installation-level by 75%, while having the best usage abilities would entail an output gain of about 80%, emissions being equal. When both sources of environmental efficiency dispersion are eliminated, the total gain is about 155%. It is reassuring to observe that the total green growth potential which, according to our estimates, would follow from a full removal of cross-installation heterogeneity in technology adoption and usage is compatible with the objectives of the "Fit for 55" strategy

[15] We use the average of the top 5% performers instead of the E-PU of the best individual installation not to have the E-PU $gain_i$ index driven by an outlier.
[16] Within-sector distributions are presented in Appendix.

lunched by the European Commission for delivering the EU's 2030 climate targets.[17] According to the most recent version of the "Fit for 55" legislative package, EU net greenhouse gas emissions are expected to be reduced by 57% by 2030 compared with 1990 levels, while preserving living standards and economic growth. Our estimated 155% potential gain in output, emissions being equal, can be also read as an about 60% reduction in emissions, output being equal. In these terms, our results appear reasonable and in line with the 2030 climate goals of the European Commission.

On the other side, we also find significant heterogeneity in the relative size of these gains across sectors. In the production of lime and dolomite, nitric acid, paper and cardboard, the cross-technology dimension of environmental efficiency dispersion is quantitatively the most significant, accounting by more than two-thirds of the total dispersion. Productions of pulp from timber, pig iron and steel are associated with much larger idiosyncratic differences. Clearly, where only one E-PF was found in our mixture model estimation, efficiency gains would come only from eliminating E-PU dispersion.

The quantification of the output gains, as reported in Table 5, should be taken with caution. As we mentioned above, when restricting our analysis to installations active both in the EU ETS Phase 1 and Phase 3, we exclude from the sample about 24.1% of installations that were active in Phase 1. Arguably, these excluded installations were the least productive or were exposed to a higher closure risk. If the use of cleaner technologies implies higher survival probability (e.g. because cleaner technologies are input-saving and therefore more cost efficient), then it is possible that environmentally more efficient firms are over-represented in our final sample. As a consequence, the output gains resulting from our empirical exercise might be under-estimated.

To help interpreting the distribution of E-PF $gain_i$ and E-PU $gain_i$ across installations and sectors, it is useful to explore whether the adoption of improved environmental technologies and usage practices follows a systematic pattern, as observed for innovative technologies and revenue-based productivity more in general by a large empirical literature (Syverson, 2011; Verhoogen, 2023). In this literature, internationalization, access to external capital, intangible capital inputs, firm size and structure, among other factors, have been found to directly impact productivity at the micro level. Following this line of study, here we look at the association between E-PF $gain_i$, E-PU $gain_i$ and a number of contemporaneous characteristics of parent companies obtained from Orbis (Bureau van Dijk, 2022).[18] In particular, we consider firm size (measured as the share of company's employees relative to the total number of employees in the sector), firm age (as the number of years since the year of incorporation), a dummy variable equal to one if the firm is listed on the stock market, and intangible capital intensity (i.e., intangible assets per employee). Moreover, by looking at the number of installations of each parent company and their location, we construct two additional dummy variables equal to one, respectively, if the installation belongs to a multi-installation firm and if the installation is located in a country different from the country of the parent company's global ultimate owner.

Formally, we regress E-PF $gain_i$ and E-PU $gain_i$ on a vector of firm-specific variables, by means of OLS over the pooled sample:

$$Y_{i,s} = \delta_1 + \mathbf{d}_2 \mathbf{X}_{i,s} + \varepsilon_{i,s}, \tag{13}$$

with $Y_{i,s}$ being alternatively E-PF $gain_i$ and E-PU $gain_i$, and where $\mathbf{X}_{i,s}$ is a vector of covariates, $\mathbf{d}_2$ the associated vector of parameters, and $\varepsilon_{i,s}$ the residuals. Statistically significant correlations emerge from this exercise, as reported in Table 6.[19]

We find correlations that are broadly consistent with our interpretation of E-PF $gain_i$ and E-PU $gain_i$ as reflecting the technology adoption and the technology usage components of environmental efficiency. Installations closer to the technological frontier (i.e. E-PF $gain_i$ is lower) belong to larger, international, and multi-installation companies. Installations belonging to an international owner and to companies with higher intangibles intensity more commonly show improved technology usage. Finally, listed firms and older firms have, respectively, lower E-PF $gain_i$ and lower E-PU $gain_i$ (but these effects show weaker statistical significance after accounting for country fixed effects).[20]

Overall, these correlations are consistent with previous evidence about firm characteristics, technological upgrades and productivity outside the environmental context (e.g., Battisti et al., 2021). A suggestive, yet speculative interpretation of this finding is that the adoption and the usage of environmental technologies are facilitated by international exposure and broader access to external funding and to higher quality inputs. Hence, firms may have improved environmental efficiency more likely when international linkages are stronger, their productive structure is broader and when the firm makes greater use of information technology and other types intangible assets. Larger and exporting firms may invest more in abatement also because they can exploit a larger scale to spread the fixed costs of abatement investment (Forslid et al., 2018; Barrows and Ollivier, 2018).

6. Robustness checks

There are two main issues that may distort the quantification of the technology adoption and technology usage components of environmental efficiency dispersion provided in the previous Section. One is the possible endogeneity bias in the E-PF estimation. The second issue relates to the specification of the E-PF itself.

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17 In particular, the Green Deal Industrial Plan (European Commission, 2023) is an articulated architecture of initiatives aimed at improving the development, diffusion and usage of clean technologies, through simplified regulations, easier access to finance, enhanced skills, and open trade.

18 We link each installation i in the EU OHA database with its parent company in Orbis by using approximate string matching (fuzzy matching), with a match rate of 82.86%. Precisely, our matching procedure exploits similarities between company names in Orbis and the names of account holders in the EU OHA database, with an account holder (i.e. the holder of a permits account) possibly covering more regulated installations belonging to a same multi-plant company. This means that balance-sheet variables at the parent company level are attached to every installation (one or more than one) of the same parent firm. Changes in ownership are not an issue, provided that they do not imply changes in company names and identification numbers.

19 Notwithstanding a good match rate between the EU OHA and Orbis databases, in the regressions with firm-level controls the number of observations drop significantly because of extensive missing data in Orbis.

20 That country effects absorb the effect of firm listing is compatible with De Haas and Popov (2023), which shows that deeper (country-level) stock markets facilitate the transition to technologies resulting in lower carbon emissions per unit of output.

Table 6
E-PF $gain_i$, E-PU $gain_i$ and parent firms' characteristics.

	[1] E-PF $gain_i$	[2] E-PU $gain_i$	[3] E-PF $gain_i$	[4] E-PU $gain_i$
Firm age	0.000	−0.001**	−0.000	−0.001
	(0.001)	(0.000)	(0.001)	(0.001)
Firm size	−1.444**	−0.419	−1.896***	−0.406
	(0.609)	(0.290)	(0.626)	(0.295)
Multi-installation firm	−0.434***	−0.020	−0.382***	−0.042
	(0.093)	(0.053)	(0.094)	(0.054)
Intangibles intensity	−0.000	−0.001**	−0.000	−0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Listed firm	−0.348*	−0.002	−0.254	−0.106
	(0.177)	(0.106)	(0.194)	(0.117)
International ultimate owner	−0.196**	−0.130**	−0.198**	−0.097*
	(0.091)	(0.052)	(0.095)	(0.056)
Constant	1.169***	0.947***	0.763***	1.334***
	(0.089)	(0.052)	(0.243)	(0.148)
Country FE	No	No	Yes	Yes
F	8.56	3.61	4.72	2.48
Pr.> F	0.000	0.001	0.000	0.000
# of obs.	493	554	493	554

Statistical significance: * = 10%, ** = 5%, *** = 1%. Standard errors are in parentheses. Installation level OLS regressions. All sectors pooled. Sectors with $\tilde{\mathcal{T}} = 1$ are omitted from the E-PF $gain_i$ regressions.

6.1. Endogeneity bias

It is well known since Marschak and Andrews (1944) that, if the firm has knowledge of its idiosyncratic efficiency parameter when making input choices, these choices will likely be dependent on such efficiency term. This is the so-called "simultaneity problem". In our environmental framework, this equals to say that both $\alpha_{i,\tau}$ and $\{\alpha_\tau, \beta_\tau\}$ in Eq. (4) may be biased due to the fact that, while the true $\alpha_{i,\tau}$ is unobserved by the econometrician, it is known by the firm when it takes emission decisions, i.e. $\ln(E_i)$ is endogenous. In this Section, we assess the impact of this simultaneity bias in our E-PF estimation.

To tackle the simultaneity problem in our analysis we rely on an instrumental variable (IV), i.e. a variable that is correlated with the installation-level emissions but does not directly enter Eq. (4) on the right-hand-side and is uncorrelated with $\alpha_{i,\tau}$. Economic intuition would suggest the price of CO_2 as a natural instrument. To use CO_2 prices as an instrument requires econometrically helpful variation in this variable. With permit pricing being homogeneous across firms under the EU ETS, in our cross-sectional estimation setting there is no such variation to exploit. Hence, we instrument emissions by means of the number of allowances allocated to installations through "grandfathering" at the start of the EU ETS in 2005. Following Directive 2003/87/EC on greenhouse gas emissions trading, in 2005 each installation eligible to enter the EU ETS was provided with a number of allowances allocated free of charge based on the installation's historical (predetermined) emissions. Fortunately for us, the number of allowances freely allocated was unexpected by polluters. Moreover, it is reasonable to assume that pollution permits influence output only through their effect on emissions. However, this instrument may violate the exclusion restriction, as historical emissions may be correlated with other time-invariant or slow-moving firm characteristics that also determined output in the 2005–2008 period. Yet, available data do not offer better suited instruments (previous literature too does not point to valid alternatives).

Denote the number of allowances allocated through "grandfathering" in 2005 as $A_{i,2005}$. We integrate our mixture model estimation of Eq. (4) with the following first stage:

$$E_i = \gamma_1 + \gamma_2 A_{i,2005} + \epsilon_i \tag{14}$$

The predicted values from Eq. (14) are used in the E-PF estimation. Then, we run again all the steps of our counterfactual analysis and obtain E-PF $gain_i$ and E-PU $gain_i$ as recomputed based on the IV estimation of the environmental efficiency terms. The OLS correlation between E_i and $A_{i,2005}$ over the pooled sample is reported in the Appendix and the final results of the counterfactual exercise in Table 7.[21]

The results are qualitatively similar to those obtained without accounting for endogeneity. In particular, we observe that the total gain in environmental efficiency due to removing both sources of efficiency dispersion is about 161%, against a total gain of about 155% obtained in our baseline estimation. In the IV version of the analysis, the model does not converge for installation data from the aluminium sector, plus we find other four sectors with only one technology. This explains why the cross-cluster dimension of efficiency dispersion is relatively lower (and the within-cluster dispersion relatively higher) than in the baseline estimates.

Fig. 4, finally, shows that the differences, respectively, between the baseline E-PF $gain_i$ and the IV-based E-PF $gain_i$ and between the baseline E-PU $gain_i$ and the IV-based E-PU $gain_i$ are not systematic.

[21] Details of the BIC-based selection of clusters and of the within-sector distribution of installations across clusters are available upon request.

Table 7
Potential output gains: IV estimates.

Sector	E-PF $gain_i$	E-PU $gain_i$	$Total\ gain_i$
Ammonia	0.000	0.447	0.447
	(0.000)	(0.357)	(0.357)
Carbon black	0.332	0.138	0.471
	(0.270)	(0.087)	(0.290)
Cement clinker	0.181	1.305	1.487
	(0.275)	(0.430)	(0.442)
Coke and coke ovens	0.000	0.931	0.931
	(0.000)	(0.491)	(0.491)
Glass	0.671	0.516	1.187
	(0.732)	(0.251)	(0.803)
Gypsum or plasterboard	0.000	0.313	0.313
	(0.000)	(0.238)	(0.238)
Lime and dolomite	0.619	0.552	1.172
	(0.808)	(0.248)	(0.898)
Mineral wool	0.922	0.483	1.406
	(0.804)	(0.278)	(0.781)
Nitric acid	0.000	2.412	2.412
	(0.000)	(1.596)	(1.596)
Other pulp	0.639	1.207	1.846
	(0.665)	(0.427)	(0.875)
Paper or cardboard	0.375	1.454	1.829
	(0.477)	(0.661)	(0.951)
Pig iron or steel	0.852	0.979	1.832
	(1.182)	(0.536)	(1.330)
Pulp from timber	2.079	2.217	4.297
	(1.370)	(0.748)	(1.246)
All sectors pooled	0.554	1.062	1.617
	(0.797)	(0.691)	(1.101)

Note. E-PF $gain_i$ quantifies the increase in Q that would be obtained by moving to the counterfactual scenario where all firms adopt E-PF*, expressed as a ratio with respect to the observed (i.e. actual) levels of Q. E-PU $gain_i$ quantifies the increase in Q that would be obtained by moving to the counterfactual scenario where all firms have E-PU*, the technology in use being equal, expressed as a ratio with respect to the observed (i.e. actual) levels of Q. $Total\ gain_i$ is the sum of E-PF $gain_i$ plus E-PU $gain_i$. E-PF $gain_i$, E-PU $gain_i$ and $Total\ gain_i$ are calculated at the installation-level and then reported in the table as sector-averages. Standard deviation in parenthesis. Estimates obtained by means of 2-stage mixture model estimation of Eq. (4). Aluminium is omitted due to non convergence in the mixture model estimation.

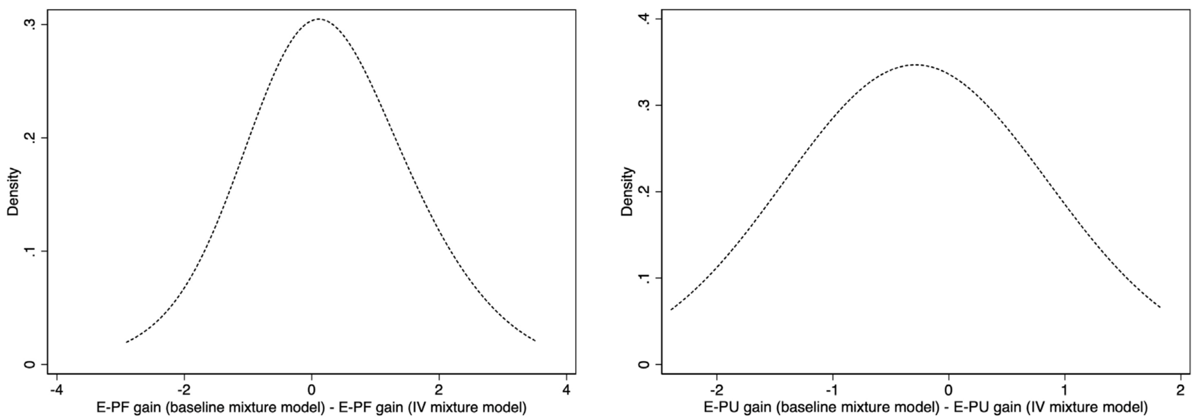

Fig. 4. Difference between baseline and IV-based E-PF $gain_i$ and E-PU $gain_i$. Note. E-PF $gain_i$ quantifies the increase in Q that would be obtained by moving to the counterfactual scenario where all firms adopt E-PF*, expressed as a ratio with respect to the observed (i.e. actual) levels of Q. E-PU $gain_i$ quantifies the increase in Q that would be obtained by moving to the counterfactual scenario where all firms have E-PU*, the technology in use being equal, expressed as a ratio with respect to the observed (i.e. actual) levels of Q. The figure displays: (left-hand panel) the distribution of the difference between E-PF $gain_i$ obtained by means of the baseline mixture model and E-PF $gain_i$ obtained by means of the IV mixture model; (right-hand panel) the distribution of the difference between E-PU $gain_i$ obtained by means of the baseline mixture model and E-PU $gain_i$ obtained by means of the IV mixture model. Pooled sample.

Table 8
Potential output gains: estimates with input-intensive E-PFs.

Sector	Capital-intensive E-PF model			Labour-intensive E-PF model		
	E-PF $gain_i$	E-PU $gain_i$	$Total\ gain_i$	E-PF $gain_i$	E-PU $gain_i$	$Total\ gain_i$
Aluminium	0.000	0.455	0.455	0.000	0.615	0.615
	(0.000)	(0.301)	(0.301)	(0.000)	(0.334)	(0.334)
Ammonia	0.004	1.861	1.865	0.000	2.235	0.235
	(0.010)	(0.653)	(0.653)	(0.000)	(0.849)	(0.849)
Carbon black	0.016	0.270	0.286	0.001	0.325	0.326
	(0.049)	(0.128)	(0.144)	(0.002)	(0.191)	(0.191)
Cement clinker	0.798	0.467	1.266	1.616	0.388	2.005
	(0.908)	(0.259)	(0.913)	(0.686)	(0.180)	(0.679)
Coke and coke ovens	0.000	0.675	0.675	–	–	–
	(0.000)	(0.531)	(0.531)	–	–	–
Glass	0.502	0.297	0.800	0.413	0.277	0.691
	(0.485)	(0.178)	(0.529)	(0.394)	(0.137)	(0.433)
Gypsum or plasterboard	0.001	0.392	0.393	0.000	0.573	0.573
	(0.001)	(0.217)	(0.218)	(0.000)	(0.348)	(0.348)
Lime and dolomite	0.331	0.252	0.584	–	–	–
	(0.553)	(0.130)	(0.605)	–	–	–
Mineral wool	0.000	0.425	0.425	0.695	0.341	1.036
	(0.000)	(0.269)	(0.269)	(0.544)	(0.236)	(0.599)
Nitric acid	0.000	1.594	1.594	0.000	1.695	1.695
	(0.000)	(1.326)	(1.326)	(0.000)	(1.475)	(1.475)
Other pulp	1.051	0.808	1.859	0.000	1.630	1.630
	(0.587)	(0.302)	(0.731)	(0.000)	(0.564)	(0.564)
Paper or cardboard	0.520	1.356	1.876	5.570	1.692	7.263
	(0.744)	(0.520)	(0.869)	(1.772)	(0.682)	(1.949)
Pig iron or steel	0.656	0.870	1.527	0.140	1.625	1.766
	(0.841)	(0.336)	(0.915)	(0.173)	(0.843)	(0.873)
Pulp from timber	1.907	0.852	2.760	0.301	0.490	0.791
	(2.168)	(0.405)	(2.245)	(0.626)	(0.327)	(0.711)
All sectors pooled	0.602	0.732	1.335	1.810	1.030	2.840
	(0.865)	(0.577)	(1.047)	(2.424)	(0.860)	(2.823)

Note. E-PF $gain_i$ quantifies the increase in Q that would be obtained by moving to the counterfactual scenario where all firms adopt E-PF*, expressed as a ratio with respect to the observed (i.e. actual) levels of Q. E-PU $gain_i$ quantifies the increase in Q that would be obtained by moving to the counterfactual scenario where all firms have E-PU*, the technology in use being equal, expressed as a ratio with respect to the observed (i.e. actual) levels of Q. $Total\ gain_i$ is the sum of E-PF $gain_i$ plus E-PU $gain_i$. E-PF $gain_i$, E-PU $gain_i$ and $Total\ gain_i$ are calculated at the installation-level and then reported in the table as sector-averages. Standard deviation in parenthesis. Estimates obtained by means of input-intensive specifications of Eq. (4). Lime and dolomite and coke and coke ovens are omitted in the labour-intensive estimates due to insufficient observations.

6.2. *Misspecification bias*

In our baseline analysis we modelled the association between output and emissions, with both variables being measured in levels. One may wonder whether our main results would have changed significantly if output and emissions were expressed per unit of capital or unit of labour. This would equal to cluster installations into technology-types defined in terms of an input-intensive version of environmental efficiency. There is not an *a priori* best way to estimate the E-PF parameters between using variables in the levels or per unit of inputs. Nevertheless, it is worth exploring whether the specification strategy we have chosen in baseline analysis drives the scale of our estimates.

Here we assess the empirical impact of our model strategy, by computing E-PF $gain_i$ and E-PU $gain_i$ as resulting from estimating Eq. (4) in an input-intensive form. We run two checks, one in which Eq. (4) is estimated with $E_{i,s}$ and $Q_{i,s}$ expressed per unit of tangible capital and one where $E_{i,s}$ and $Q_{i,s}$ are expressed per unit of labour. These two specifications model the relationship between emissions and output with capital and labour, respectively, being equal. Data on capital and labour inputs are taken from the balance sheets of parent companies in Orbis. The regression analysis uses the sub-sample of installations for which we have a match between EU OHA and Orbis records.

The results are displayed in Table 8. Again, we obtain technological and idiosyncratic environmental efficiency differentials in line with our baseline estimates. Since data on labour inputs are missing for many firms in two sectors in particular (lime and dolomite, coke and coke ovens), in these sectors we remain with an insufficient number of observations to run our regressions. Moreover, we obtain exceptionally large values of E-PF $gain_i$ in the paper and cardboard industry, which drive the pooled average up. For all the other sectors, both E-PF $gain_i$ and E-PU $gain_i$ obtained here are qualitatively similar to those resulting from considering our baseline version of Eq. (4).

7. Conclusions

In recent years, there has been increasing attention to the development of empirical strategies aimed at exploring within-product heterogeneity in productivity and its relationship with technical change (e.g., Dosi et al., 2016; Battisti et al., 2020; Dosi et al., 2021). In this literature, less effort has been devoted to measuring the environmental dimension of such productivity differentials. To which extent do firms in a same product market differ in how they combine marketed and non-marketed outputs? And to which extent can these differences be interpreted as differences in the type of technology adopted by otherwise similar firms? How large are the potential gains from broadening the diffusion of frontier technologies and how large those from improving the way a same technology is used? These questions are relatively new, but they are already very relevant for both industrial policy and environmental regulation, as the ongoing design of technology transition plans in Europe and the US, in addition to other countries and regions, revolves around the possibility to link economic growth and improved environmental sustainability of industrial productions—the so-called "green growth".

With this paper we digged into these issues. We applied a mixture model technique on installation-level data to decompose environmental efficiency into a technology adoption (group-level) and a technology usage (installation-level) component. This method has two main attractive properties: (*i*) it is entirely data-driven (i.e. it does not need assumptions on the number of technology-types available in the sector and on the degree of technological sharing across installations), and (*ii*) it only requires information on emissions and output levels, which is typically available for large-scale samples of firms (in our exercise, we used freely accessible data from the EU OHA database). Moreover, by working at the installation-level, our empirical analysis allows different installations to adopt different types of technology, even within the boundaries of a same parent company.

Our study yields the general result that cross-sectional differentials in both technology adoption and technology usage are qualitatively important in many sectors. We find that more than two-thirds of regulated installations in our European sample uses sub-optimal technologies, whereas adopting the locally optimal technology-type would lead on average to a 75% increase in output, emissions being equal. Interestingly, the distribution of both cross-technology and within-technology differences tends to be associated with several firm characteristics, with within-technology asymmetries on average being lower for the production units at the technological frontier.

Related literature on environmental technology adoption has explored a number of possible causes leading firms not to adopt improved environmental technologies. In particular, some of these technologies may not be profit enhancing and adopting them may be inconvenient for profit-maximizing firms, absent public policy. Others may be profitable (e.g. because they are energy-saving) but their adoption may be prevented by transaction costs, monitoring costs, administrative costs and adjustment costs (De Canio and Watkins, 1998), which may be critical especially for firms with reduced access to external finance (D'Orazio and Valente, 2019; De Haas et al., 2021; De Haas and Popov, 2023).[22] Also the lack of complementary technologies and skills may retard the adoption of low-carbon energy technologies (Popp et al., 2022). Related to this, in addition it has been shown that the timing of adopting socially efficient technologies may be affected by disruption costs and market structure (Milliou and Petrakis, 2011; Pérez and Ponce, 2015).

Our paper adds to this literature in two distinct ways. First, it provides an easy to implement algorithm to quantify the potential gains in output, emissions being equal, that can be reached by boosting emission-saving technology diffusion. With our method, this quantification can be done at the most granular level, i.e. the installation level.

Second, the paper shows that there is a great variability across regulated installations (even within countries and sectors) in technological quality, with many capped installations adopting sub-optimal technologies and others adopting optimal (or close to optimal) technologies together with environmentally inefficient usage practices. We show that these asymmetries tend to be systematic and aligned with existing evidence on the competitive advantages of multinational firms. Our findings may suggest that existing technologies have large unexploited potentials, particularly among smaller, national firms. Arguably, our method could stimulate future research to explore more deeply the causes of such heterogeneity.

Taken together, these findings point to technology diffusion as an important target for environmentally oriented industrial policy. In particular, we find that what is an optimal technology-type, in terms of environmental efficiency, depends on the installation's level of emissions. On the one side, we observe that the technologies with the highest shape parameter (i.e. β) tend to be sub-optimal at low levels of emissions. Viceversa, the technologies that are most efficient at low levels of emissions tend to be less so for higher levels of pollution. As a result, assuming that emission levels and installation size correlate positively, one-size-fits-all technology standards may be inappropriate for some installations and less effective, on average, than emission-contingent technology prescriptions. In different words, certain technologies may fit better for smaller firms, whilst larger firms may perform better under different technological choices. In terms of policy, this points to implementing more targeted technology measures rather than uniform prescriptions. This holds if the size of the firm is taken as given by policy-makers. On the other side, we show that the technologies with the highest β parameter are those associated with the highest Q-to-E ratio above and to the right of the kink point (where the E-PFs intersect), i.e. for installations above a certain critical size. Hence, if policy-makers can affect the size of production installations, it is optimal for policy-makers to design industrial policies that both spur installation growth and at the same time facilitate technology switching towards high-β technologies. That is, provided that installations are above a critical size, uniform standards may be imposed.

Our findings also lend support to the adoption of flexible policies, that combine technology standards with market-based regulations inducing each firm to work more on the margin (adoption or usage) where the scope for improvement is larger. In this respect, it is worth emphasizing that our analysis is conducted on a sample of installations regulated under the EU ETS, which is a type of market-based regulation that is supposed to be effective in spurring environmental efficiency. Indeed, under a cap-and-trade

[22] A broader body of study on economic productivity dispersion shows that informational frictions and adjustment costs may be an important driver of such dispersion, which could in fact be optimal within the context of richer models (Asker et al., 2014).

program, firms should react to a higher price of emissions by making operational changes and investments in technologies with reduced emission intensity. In the language of our framework, firms below the technological frontier should find it more convenient to adopt more efficient technologies if there is no room for improving usage practices further. Viceversa, firms at the technological frontier may be induced to adopt improved usage practices. Since our empirical study is based on data from EU ETS Phase 1, taking a picture at the very beginning of the program, a simple and informative policy evaluation exercise may be conducted by re-running our model on more recent data to measure the extent to which the EU ETS has induced environmental efficiency improvements on the two margins of technology adoption and usage.[23] Unfortunately, a policy impact research of this kind would require information on installation-level physical product-output that is not disclosed by the European Commission.[24] It is worth noting that, when information on both emission and output is available, our method may be used to conduct policy evaluation analysis over a broad range of regulatory issues beyond emission trading programs.

Future research may also consider refining our method in the direction of enabling it to identify the nuances of technology types more precisely. Our method identifies groups of technologies that differ in terms of output-to-emission rates, clustering together technologies with a same environmental impact (per unit of output) even if they are different in their physical characteristics and degree of sophistication. These within-group differences, however, may correlate with other important dimensions, such as different cost functions or differences in the labour skills required as complementary assets. A proper design of technology policy interventions may need more detailed information about these sources of within-group heterogeneity, which are not captured with our technique. Although this aspect may be seen as a limit of our method, we believe that it is also a useful trigger possibly stimulating additional work on the measurement of environmental technology heterogeneity.

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Declaration of competing interest

We hereby declare that:

We did not benefit from any source of financial support for the particular research the paper describes;

There is no interested party to declare, from whom we received significant financial support, summing to at least $10,000 in the past three years, in the form of consultant fees, retainers, grants and the like;

We did not act in any paid or unpaid positions as officer, director, or board member of relevant non-profit organizations or profit-making entities (and this also applies to any close relative or partner of mine);

No other party had the right to review the paper prior to its circulation.

Appendix

A.1. Additional tables and figures

See Tables 9–12 and Figs. 5 and 6.

Data availability

EUTL data used in this paper and replication codes can be made available upon request.

23 With reference to the EU ETS, Marin et al. (2018) and Dechezlepretre et al. (2023) compare the performance of regulated and non-regulated firms over a set of indicators, including carbon emissions and economic productivity, without digging into the changes in environmental efficiency of regulated units across the phases of the EU ETS. Calel (2020) documents that the EU ETS has not encouraged the diffusion of low-carbon technologies to any substantial extent, but he does not show whether regulated firms improved on other margins, such as technology usage or managerial quality.

24 Recall that we obtained the average output levels for the period 2005–2008 by inverting the allowance allocation rule employed in the EU ETS Phase 3.

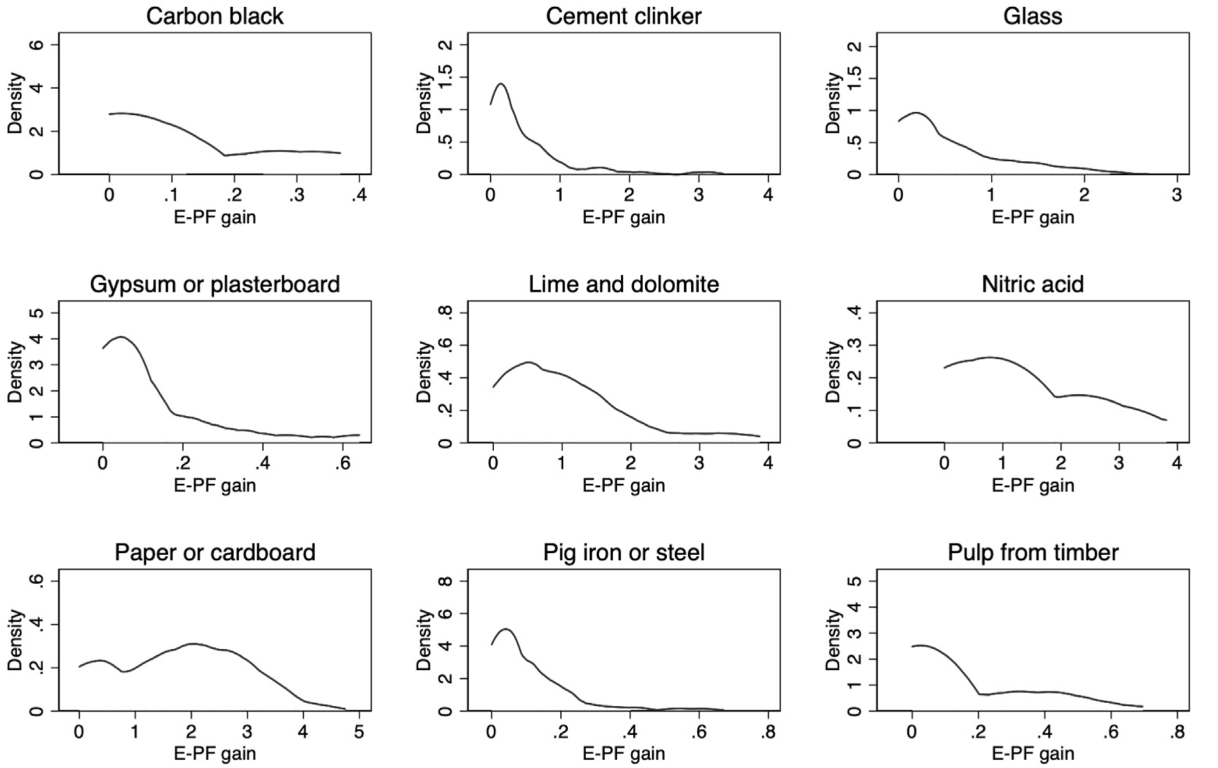

Fig. 5. Distribution of E-PF $gain_i$ within sectors. Note. E-PF $gain_i$ quantifies the increase in Q_i that would be obtained by an installation by switching to E-PF$_{\tau^*}$, expressed as a ratio with respect to the observed (i.e. actual) levels of Q_i. Sectors with $\tilde{\mathcal{T}} = 1$ are omitted.

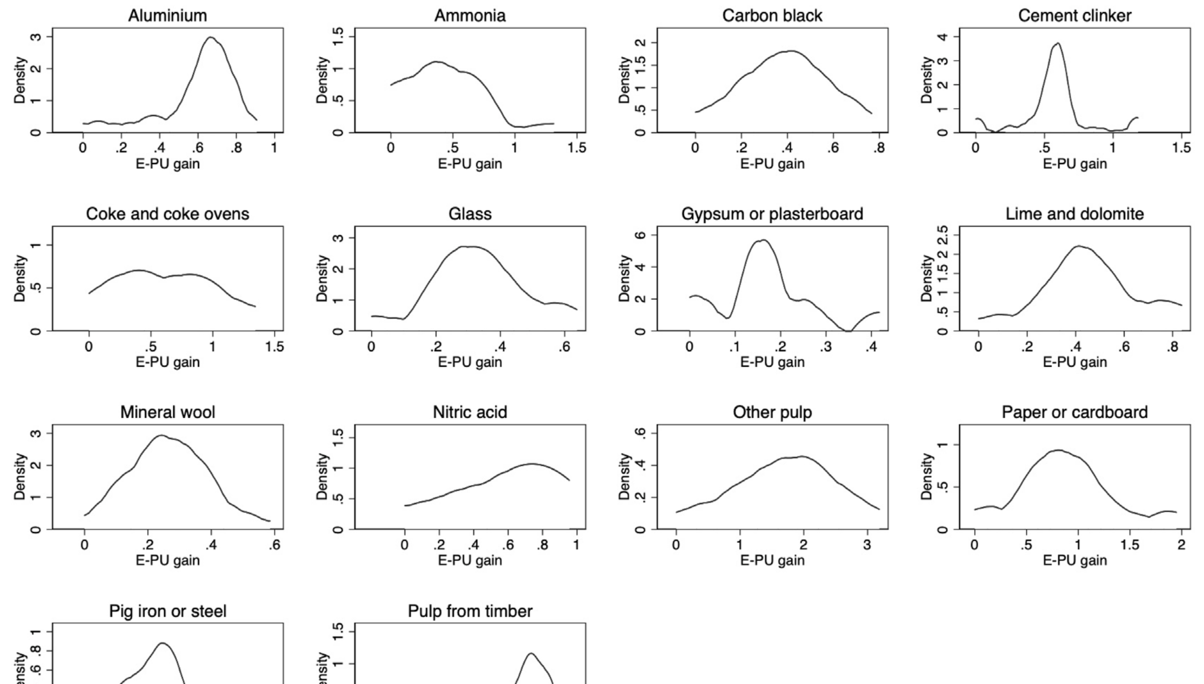

Fig. 6. Distribution of E-PU $gain_i$ within sectors. Note. E-PU $gain_i$ quantifies the increase in Q_i that would be obtained by an installation by having the same E-PU as the average of the top 5% performers, the technology in use being equal, expressed as a ratio with respect to the observed (i.e. actual) levels of Q_i.

Table 9
CSCF and CLEF.

Year	ϑ_t (CSCF)	$\lambda_{s,t}$ (CLEF) sectors at risk of carbon leakage	$\lambda_{s,t}$ (CLEF) sectors not at risk of carbon leakage
2013	0.94272151	1	0.8000
2014	0.92634731	1	0.7286
2015	0.90978052	1	0.6571
2016	0.89304105	1	0.5857
2017	0.87612124	1	0.5143
2018	0.81288476	1	0.4429
2019	0.79651677	1	0.3714

Note. The carbon leakage exposure factor — CLEF ($\lambda_{s,t}$) is constant 1 or decreasing at a predetermined rate depending on the carbon leakage status of the sector. The cross-sectoral correction factor — CSCF (ϑ_t) ensures that total allocation remains below the maximum amount pursuant to article 10a(5) of the EU ETS Directive (European Commission, 2015).

Table 10
List of sectors, benchmark emission intensities and carbon leakage risk.

s-sector (EU-OHA classification)	Product-specific benchmark emission intensity	$\tilde{e}_s$	Exposure to carbon leakage risk
Aluminium	Aluminium: 1.514	1.514 (1-to-1 match)	Yes
Ammonia	Ammonia: 1.619	1.619 (1-to-1 match)	Yes
Carbon black	Carbon black: 1.954	1.954 (1-to-1 match)	No
Cement clinker	White cement clinker: 0.766 Grey cement clinker: 0.987	0.876 (average)	Yes
Coke and coke ovens	Coke and coke ovens: 0.286	0.286 (1-to-1 match)	Yes
Glass	Float glass: 0.453 Colourless glass: 0.382 Coloured glass: 0.306	0.380 (average)	Yes
Gypsum or plasterboard	Plaster: 0.048 Gypsum: 0.017	0.032 (average)	Yes (No in 2013-14)
Lime and dolomite	Lime: 0.954 Dolomite: 1.072	1.013 (average)	Yes
Mineral wool	Mineral wool: 0.682	0.682 (1-to-1 match)	No
Nitric acid	Nitric acid: 0.302	0.302 (1-to-1 match)	Yes
Other pulp	Sulphite pulp: 0.020 Short fibre kraft pulp: 0.120 Long fibre kraft pulp: 0.060	0.067 (average)	Yes
Paper or cardboard	Coated fine paper: 0.318 Uncoated fine paper: 0.318 Coated carton board: 0.273 Uncoated carton board: 0.237	0.286 (average)	Yes
Pig iron or steel	Pig iron or steel: 0.325	0.325 (1-to-1 match)	Yes
Pulp from timber	Pulp from timber: 0.039	0.039 (1-to-1 match)	Yes

Note. Product-specific benchmark emission intensities are listed in European Commission (2011) according to a classification that is more granular than the EU-OHA sectors classification. We cross-walked the two classifications using product-sector description matching: (i) 1-to-1 match is obtained when product and sector descriptions perfectly coincide, (ii) where different products covered by a larger EU-OHA sector have different product-specific benchmark emission intensities, the sectoral benchmark emission intensity $\tilde{e}_s$ is obtained as the average of the product-specific benchmark emission intensities. Unmatched sectors are left out of the analysis.

Table 11
Summary of the actual emission-relevant production processes.

s-sector ($\tilde{\mathcal{T}}$)	Actual processes (EPA, 2022)
Aluminium (1)	The production of aluminium consists of refining the ore and electrolytically reducing it to elemental aluminium. Nearly all alumina refineries use the Bayer process integrated with wet scrubber systems.
Ammonia (1)	Most ammonia is produced by means of the Haber process, with activated carbon fortified with metallic oxide additives used for feedstock desulfurization. CO_2 is removed from the synthesis gas by scrubbing.
Carbon black (2)	Two major processes are available: the oil furnace process and the thermal process. The principal source of emissions in the oil furnace process is the main process vent, but most gaseous emissions can be controlled with CO boilers, incinerators, and flares. Emissions from the furnaces in thermal process are very low.
Cement clinker (3)	Three main different processes are used in the cement industry to accomplish pyroprocessing: wet production technology, semi-wet or semi-dry technology, dry technology. Fuel consumption decreases in the order of the three processes listed, with the combustion of fuels being a main source of CO_2 in this industry.
Coke and coke ovens (1)	Coke is typically produced by the destructive distillation of coal in coke ovens, mostly using the “byproduct” process in the period under analysis. Emissions can be controlled at various steps of the process.
Glass (5)	Commercially produced glass are typically classified in five types: soda-lime, lead, fused silica, borosilicate, and 96-percent silica. The melting furnace contributes over 99% of the emissions from a glass plant, with the amount of emissions from the melting furnace depending upon the type of glass being manufactured.
Gypsum or plasterboard (2)	Production of gypsum board consists of calcining and grinding gypsum powder, forming a gypsum panel product and drying off excess water. Heating can be performed in two alternative ways with different emission rates: by using kettle or flash calciners, or by using heated impact mills which eliminate the need for rotary dryers, calciners, and roller mills.
Lime and dolomite (4)	Lime and dolomitic lime are manufactured with one among four kinds of kilns, which are at the heart of the plant: rotary kiln, vertical or shaft kiln, calcimatic kiln and fluidized bed kiln. Calcimatic and fluidized bed kiln do not operate with coal. Fuel efficiency varies significantly across the four types of kilns.
Mineral wool (3)	The main step in the process of mineral wool manufacturing involves melting the mineral feed, by loading the raw material into a cupola, which is the primary source of emissions, as it requires burning coke. This process can be modified to reduce coke consumption and emissions, by using natural gas auxiliary burners or an aluminium flux byproduct.
Nitric acid (2)	Nitric acid is produced by two methods, i.e. by utilizing oxidation, condensation, and absorption, or by combining dehydrating, bleaching, condensing, and absorption. Depending on the method, control of absorption tower tail gas emissions is obtained with extended absorption or with catalytic reduction.
Other pulp (1)	This is mostly kraft pulping, with emissions occurring largely from the recovery furnace. Emission control is generally accomplished by scrubbers.
Paper or cardboard (2)	In the production of paper and cardboard, two process can be distinguished. Both begin with the pulping of wood chips in the kraft process. One process continues with refining, sizing, colouring of the fibres, and later forming paper sheet in a Fourdrinier machine. The other uses corrugators to crimp and glue layers of kraft paper to form corrugated cardboard.
Pig iron or steel (2)	Iron is produced in blast furnaces by the reduction of iron bearing materials with a hot gas. The subsequent steelmaking process can be performed by using a basic oxygen furnace, where high-purity oxygen is injected, or by electric arc furnaces. The two methods have different emissions rates.
Pulp from timber (2)	Pulping from timber refers to the process of separating the wood fibre and removing impurities from the fibre materials. The two typical methods involve chemical or mechanical processes (with or without using heat), with different emission rates.

Table 12
First stage OLS correlation between emissions and allowances.

γ_1	γ_2	R^2	F	Pr.> F
7526.502* (3979.685)	0.916*** (0.005)	0.953	23 883.36	0.000

Note. Statistical significance: * = 10%, ** = 5%, *** = 1%. Standard errors are in parentheses. Installation level OLS regression. All sectors pooled.

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