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Summary

We propose a mixture model approach to identify locally optimal technologies and to dissect environmental productivity (output produced per unit of emission) into a technological and a managerial component. For a large sample of plants covered by the EU ETS, we find that the share of plants adopting the frontier technology is about 21%. We also find that the average output gains that plants could reach by adopting optimal technologies and managerial practices are 75% and 80% respectively. These results remain qualitatively similar after addressing endogeneity of emissions. Finally, we match EU ETS data with balance-sheet data on parent companies and find that better environmental technologies tend to be adopted by larger, listed, multi-plant and international companies, while older firms and firms with higher intangibles assets intensity more commonly show improved environmental management. Our results suggest that existing technologies have large unexploited potentials and deliver important insights for policy.

Keywords: Environmental productivity, Emission intensity, Environmental technology, Environmental management

JEL Classification: D24, L60, Q54, Q55

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Digging into the Technological Dimension of Environmental Productivity

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Abstract

We propose a mixture model approach to identify locally optimal technologies and to dissect environmental productivity (output produced per unit of emission) into a technological and a managerial component. For a large sample of plants covered by the EU ETS, we find that the share of plants adopting the frontier technology is about 21%. We also find that the average output gains that plants could reach by adopting optimal technologies and managerial practices are 75% and 80% respectively. These results remain qualitatively similar after addressing endogeneity of emissions. Finally, we match EU ETS data with balance-sheet data on parent companies and find that better environmental technologies tend to be adopted by larger, listed, multi-plant and international companies, while older firms and firms with higher intangibles assets intensity more commonly show improved environmental management. Our results suggest that existing technologies have large unexploited potentials and deliver important insights for policy.

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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 (2020)). Looking at the plant-level, the decline of emission intensity seems to be driven primarily by a within-product increase in environmental productivity, 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 other output-based measures of productivity, environmental productivity remains highly dispersed even within narrowly defined industries. This has important economy-wide consequences because, in response to aggregate shocks (like an exogenous increase in input prices), microeconomic heterogeneity may amplify macroeconomic dynamics thereby leading to fluctuations in the aggregate environmental performance of firms beyond the effect of the initial shock. In particular, it is still poorly understood whether cross-plant differentials in environmental productivity are to be explained mainly in terms of differences in the technology used by different groups of firms or as idiosyncratic differences in managerial practices across firms using the same technology. Quantifying these dimensions has broad policy implications, as it would help evaluating the potential gains of technology diffusion policies in comparison with policies aimed at improving environmental management.[1]

The main reason of this lacuna is practical. Measuring the technological dimension of

[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), whereas policies aimed at promoting environmental management are typically more nuanced and point to improving managerial skills, environmental awareness, green accounting and, more in general, corporate social responsability.

environmental productivity requires estimating as many production functions as the different production technologies available in a sector, in order to obtain technology-specific emissions coefficients. Under standard techniques, this is possible only after conducting some form of clustering, e.g. based on an engineering approach with experts examining and classifying the technology in use firm-by-firm. Such approaches are clearly unusable on a large scale. On the other hand, obtaining residual TFP-like measures of environmental productivity under the assumption that a single technology (i.e. production function) exists in a sector implies confounding the firm-specific (managerial) and the group-specific (technological) dimensions of environmental productivity. This is one of the reasons why research that studies the environmental performance of management employs measures of managerial quality obtained from outside production data, typically from surveys (e.g., Bloom *et al.* (2010), Martin *et al.* (2012)).

In this paper we use an innovative methodology to decompose plant-level environmental productivity into a technological and a managerial dimension.

We use data on plant-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 plants regulated under the EU Emission Trading System (EU ETS). 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 plant. 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.

Next, our analysis proceeds in two main steps. We first employ an empirical mixture model to identify different "environmental-production functions" (E-PFs) within narrowly defined industries. The estimation determines the number of E-PFs available in a sector, with each E-PF reflecting an environmental production technology defined in terms of physical output generated per unit of emissions. The model leaves the estimation free to determine both the number of E-PFs available in each sector and the probability of each plant using each E-PF. Hence, the estimation provides us, for each sector, with the number of available environmental technologies and, for each plant, with the probability of adopting each technology, including the one reflected into the frontier E-PF (i.e. associated with the minimum emission intensity). Brought to our data, this exercise delivers a number of technologies ranging from one to five, with most sectors having more than one technology. We then use the difference between the observed output of each plant and the estimated output associated with each E-PF to compute a plant-level measure of "environmental-total factor productivity" (E-TFP), weighted by the plant's probability of adopting each available technology. The E-TFP can be interpreted as the idiosyncratic (i.e. managerial) component of the environmental performance of a plant, given the production technology.[2] In the sectors where more than one technology is available, we find that the probability weighted share of plants adopting the frontier technology is about 21% and that the dispersion of the E-TFP varies substantially depending on the technology in use (with the E-TFP variance being in most sectors lower for the firms using the frontier technology).

Second, we quantify the potential gains in environmental productivity from eliminating technological and managerial heterogeneity. We compute two counterfactual scenarios. One in which the plant adopts the frontier E-PF available in its sector and one in

[2] Previous productivity research has shown that the Solow residual in production function estimation is largely accounted for by idiosyncratic managerial quality (e.g., Bhattacharya *et al.* (2013)).

which the plant continues to be attached to the probability of adopting each technology as estimated in the first step but shows the E-TFP of the top 5% performers in the sector. For each plant, 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 would increase average output at the plant-level by 75%, while using the best managerial practices would entail an output gain of 80%, emissions being equal. On average, the total gain from technology upgrades when both sources of productivity dispersion are eliminated is about 155%.[3] Behind these averages, we also document that the growth margins of environmental productivity differ substantially both across sectors and across plants within sectors, partly reflecting a number of variables on parent companies obtained by linking each plant in the EU OHA database with its parent company in Orbis (Bureau van Dijk, 2022). In particular, we find that better environmental technologies are more likely to be adopted by larger, listed, multi-plant and international companies, while older firms and firms with higher intangibles assets intensity more commonly show improved environmental management.

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 management of currently used 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 practices. Moreover, by unveiling significant cross-plant asymmetries in the sources of the environmental productivity gaps, our statistical decomposition leads to consider market-based regulations as the preferred

[3]In the Appendix, we show that these results are qualitatively unchanged when plant-level emissions are modeled as an endogenous variable in the production function mixture estimation.

way for improving environmental productivity—an insight in line with the "narrow" version of the so-called Porter Hypothesis (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 technological and the managerial components of environmental productivity dispersion. Section 6 concludes by explaining the policy relevance of our analysis.

2 Related literature

The paper is at the intersection of three 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.* (2009) provide an extensive survey of this literature. More 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 (2020) 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. Macher *et al.* (2020) show that the effect of environmental regulatory constraints on energy-saving technology adoption is greater in more competitive environments. In the European context, 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. On the same vein, Borghesi *et al.* (2020) show that the EU ETS had a weak effect on firm-level patterns of investments abroad through the opening of new subsidiaries. This literature has improved our understanding of the process of environmental technologies diffusion, particularly in regulated contexts such as the one considered in our paper. However, it does not explore the technological differentials across regulated firms. 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. The methodology proposed in the present paper allows to address this gap.[4]

Second, our paper adds to the literature on the environmental consequences of managerial quality. 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). In fact, the quality of the management has been found to correlate positively with the environmental performance of the company by recent studies. 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 climate friendly management practices are associated with lower energy intensity and higher productivity. De Haas *et al.* (2021) show that managerial constraints slow down

[4]Incidentally, 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 (2022) for an overview).

firm investment in more energy efficient and less polluting technologies, using data for a large sample of firms in 22 emerging markets. We contribute to this line of research, by measuring the potential environmental productivity gains that can be obtained by spreading improved managerial practices among polluting firms.

Finally, our paper relates to the literature on productivity estimation. A broad array of methods of productivity measurement is available (Del Gatto *et al.* (2011) and Van Beveren (2012) provide comprehensive surveys of these methods). However, this literature almost exclusively focuses on the relationship between marketed inputs and outputs, while little effort has been put into the development of methods focused on non-marketed inputs (e.g. environmental quality) since the notion of environmental productivity was introduced (Repetto, 1990). In this paper, we operationalize an environmental production function where the notion of productivity is expressed as marketed output per unit of emissions. In doing this, we develop an empirical mixture method similar in spirit to the one proposed by Battisti *et al.* (2015) and Battisti *et al.* (2020) in a more classical TFP context, which allows for the probability distribution of environmental productivity to be the result of the potential overlapping of several distributions that we then interpret as different environmental technologies. This estimation strategy, more generally, contributes to enriching the line of methodological research in industrial economics that analyzes the determinants of cross-firm productivity differentials (see Syverson (2011) for a review), and in this literature, in particular, adds to the body of works exploring quantity-based measures of productivity (e.g., de Roux *et al.* (2021)). In addition, by exploiting plant-level granularity, our analysis improves also on the standard revenue-based production function estimation literature, which commonly uses data aggregated at the firm-level.

3 Data

We use plant-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. The database provides accurate information on tons of verified CO_2-equivalent emissions and the number of allocated emission permits for each plant and year covered by the EU ETS, along with information on the plant's location and product sector.

We are able to retrieve plant-level output from the inverse 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 plant 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 Equation (1).[5] Plant-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, a plant's

[5] 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. We remain with 1881 plant-level observations. Details on CLEF, CSCF and benchmark emission intensities are provided in the Appendix.

emission intensity can be calculated as:

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

Environmental productivity is nothing else than the reciprocal of $e_{i,s}$.

The cross-sectional distribution of e_i within each sector is illustrated in Figure 1.[6] As the figure shows, there are significant emission intensity differentials across plants. The sense of scale of these differentials can be grasped by considering that, in most of the sectors, the emission intensity of the plant at the 75-th percentile of the distribution is about as twice as the emission intensity of the plant at the 25-th percentile.

[insert Figure 1 about here]

While this evidence suggests that dispersion of environmental productivity is significant even in narrowly defined industries, it reveals little as to whether this heterogeneity is driven by plant-specific (managerial) or group-specific (technological) sources. This is explored next.

4 Environmental production functions estimation

The environmental-production function (E-PF) of plant i is:

$$\ln(Q_i) = \alpha_{i,\tau} + \alpha_\tau + \beta_\tau \ln(E_i), \tag{3}$$

[6]The countries covered are: Austria, Belgium, Bulgaria, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Romania, Slovak Republic, Slovenia, Spain, Sweden, United Kingdom.

where τ denotes the technology adopted by plant i among the $\mathcal{T}$ technologies available in sector s. The parameters α_τ and β_τ are the constant and shape coefficients of the τ-technology's E-PF. Hence, in this framework technology τ in sector s is defined by the set $\{\alpha_\tau, \beta_\tau\}$. The residual productivity term is $\alpha_{i,\tau}$, which reflects the idiosyncratic deviation of plant i's output with respect to the fitted output of the plants adopting the same technology τ. We refer to $\alpha_{i,\tau}$ as the environmental-total factor productivity (E-TFP), which, net of the technological dimension, can be thought of as representing the plant-specific managerial component of environmental productivity. Essentially, Equation (3) describes the process through which a plant converts emissions into output abstracting away from the quantity of capital and labour used, in a similar way as standard production functions describe the relation between output and marketed inputs abstracting away from the environmental consequences of production.

We obtain α_τ and β_τ by estimating Equation (3) with a finite mixture model (McLachlan *et al.*, 2019) sector-by-sector. Under such type of modeling, the within-sector distribution of $\ln(Q_i)$ is the average of $\mathcal{T}$ distributions, each with own mean μ_τ and variance σ^2_τ, weighted by the ex-ante probabilities π_τ of belonging to group τ, i.e.:

$$f\left(\ln(Q_i)|\mu, \sigma^2\right) = \sum_{\tau=1}^{\mathcal{T}} \pi_\tau f_\tau \left(\ln(Q_i)|\mu_\tau, \sigma^2_\tau\right), \tag{4}$$

where

$$\pi_\tau = \frac{\sum_{i=1}^{N} p_{i,\tau}}{\sum_{\tau=1}^{\mathcal{T}} \sum_{i=1}^{N} p_{i,\tau}}, \tag{5}$$

with N being the number of plants 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 Equation (3). In the expectation (E) step, posterior probabilities $p_{i,\tau}$ are computed as

$$p_{i,\tau} = \frac{\pi_\tau f_\tau\{\ln(Q_i)|\mu_\tau; \sigma_\tau^2\}}{\sum_{\tau=1}^{\mathcal{T}} \pi_\tau f_\tau\{\ln(Q_i)|\mu_\tau; \sigma_\tau^2\}}, \tag{6}$$

starting from random values of π_τ. In the maximization (M) step, the likelihood for Equation (3) is maximized using observation weights:

$$\gamma_{i,\tau} = \sqrt{p_{i,\tau}}. \tag{7}$$

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.

We leave the model free to choose, in each sector, the number of technologies that best fits the data. We do so by running the mixture model estimation of Equation (3) repeatedly, imposing in each round a different number of technology clusters $\mathcal{T} \in [1, 10]$ and selecting the number of clusters that minimizes the Bayesian information criterion (BIC).[7] We denote with $\tilde{\mathcal{T}}$ such optimal number. Detailed results of our BIC-based selection procedure are collected in Table 1.

[insert Table 1 about here]

Table 2 reports the estimated α_τ and β_τ coefficients for the $\tilde{\mathcal{T}}$ technologies identified in each sector. As shown in the table, our mixture model estimation delivers a number of

[7] 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.

technologies ranging from one to five, with most sectors having more than one technology. While the emission coefficient β_τ is generally lower than one, a few technologies have β_τ greater than one. All the technology-specific E-PFs are plotted in Figure 2.

[insert Table 2 about here]

[insert Figure 2 about here]

Once the parameters describing each technology are obtained, we are able to identify the locally optimal technology τ^*, referred to as the technology such that $\ln(\hat{Q}_{i,\tau^*})|E_i > \ln(\hat{Q}_{i,\tau})|E_i \ \forall\tau \neq \tau^*$.[8] 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 Figure 2, in most sectors, we observe that there is not a unique optimal technology 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 plants.

For each plant we have the probability $\tilde{p}_{i,\tau}$ of adopting each technology τ as well as the probability $\tilde{p}_{i,\tau^*}$ of adopting the locally optimal technology 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-technology distribution of plants vary considerably both within and across sectors. In particular, in the sectors where $\tilde{\mathcal{T}} \geq 2$, the within-sector share of plants adopting technology 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.

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

When plants from all sectors are pooled, the share of plants at the technological frontier is 31.85%. The full technology-sector distributions are provided in Table 3. This result unveils that the accessibility of the frontier technology may differ remarkably across industries, with most plants in most sectors using sub-optimal technologies.

[insert Table 3 about here]

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

$$\ln(Q_i) - \sum_{\tau=1}^{\tilde{\mathcal{T}}} \tilde{p}_{i,\tau} \ln(\hat{Q}_{i,\tau}), \tag{8}$$

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

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

$$\alpha_{i,\tau^*} = \ln(Q_i) - \tilde{p}_{i,\tau^*} \ln(\hat{Q}_{i,\tau^*}) \qquad \text{and} \qquad \alpha_{i,\tau\neq\tau^*} = \ln(Q_i) - \sum_{\tau\neq\tau^*} \tilde{p}_{i,\tau} \ln(\hat{Q}_{i,\tau}), \tag{9}$$

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 use of the frontier technology may help to reduce cross-plant differentials in managerial environmental 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).

[insert Table 4 about here]

5 Gains from eliminating environmental productivity dispersion

In this section, we conduct a counterfactual exercise to give a sense of magnitude of the economic significance of the technological and the managerial dimensions of environmental productivity.

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

$$\text{E-PF } gain = \ln(\hat{Q}_{i,\tau^*}) - \sum_{\tau=1}^{\tilde{\mathcal{T}}} \tilde{p}_{i,\tau} \ln(\hat{Q}_{i,\tau}), \tag{10}$$

In simple words, E-PF *gain* measures the increase in output that would be associated with a switch to the technological frontier, the plant's E-TFP being zero.

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

$$\text{E-TFP } gain = \alpha^* - \alpha_{i,\tau} \tag{11}$$

where $\alpha_{i,\tau}$ is defined as in (8) and α^* is the average $\alpha_{i,\tau}$ of the best 5% of plants in the within-sector distribution of $\alpha_{i,\tau}$.[9]

As a difference between logarithmic terms, both E-PF *gain* and E-TFP *gain* can be directly interpreted as output gains in percentage points. By construction, the sum of E-PF *gain* plus E-TFP *gain* is the total environmental productivity distance from the "frontier installation", referred to as the installation in the top 5% performers in terms of E-TFP that adopts the locally optimal technology. Denote the sum E-PF *gain* + E-TFP *gain* with $Total\ gain$.

Table 5 reports the sectoral averages of E-PF *gain*, E-TFP *gain* and $Total\ gain$.[10]

[insert Table 5 about here]

Two main results emerge. On the one side, both the technology and the managerial dimensions are associated with economically significant productivity dispersion. In particular, switching to the frontier technology would increase average output at the plant-level by 75%, while using the best managerial practices would entail an output gain of about 80%, emissions being equal. When both sources of productivity dispersion are eliminated, the total gain in environmental productivity is about 155%.[11] Interestingly

[9]We use the average of the top 5% performers instead of the E-TFP of the best individual plant not to have the E-TFP *gain* index driven by an outlier.

[10]Within-sector distributions are presented in the Appendix.

[11]In the Appendix, we assess how these results change after addressing a possible simultaneity bias in the mixture model estimation of the production function. Instrumental variable estimates produce total potential gains in environmental productivity similar to those obtained without accounting for endogeneity.

enough, we find that the potential gains from eliminating managerial quality dispersion account for about 50% of total environmental productivity gains, that is more than previous quantifications of the management share of revenue based TFP dispersion (Bloom *et al.*, 2016).

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 technology dimension of environmental productivity 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, productivity gains would come only from eliminating E-TFP dispersion.

To help interpreting the distribution of E-PF *gain* and E-TFP *gain* across plants and sectors, it is useful to explore whether the adoption of improved environmental technologies and managerial practices follows a systematic pattern, as observed for innovative technologies and revenue-based TFP more in general by a large empirical literature (Syverson, 2011; Verhoogen, 2022). 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*, E-TFP *gain* and a number of contemporaneous characteristics of parent companies obtained from Orbis (Bureau van Dijk, 2022).[12] 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

[12] We link each plant 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%.

is listed on the stock market, and intangible capital intensity (i.e., intangible assets per employee). Moreover, by looking at the number of plants of each parent companies and their location, we construct two additional dummy variables equal to one, respectively, if the plant belongs to a multi-plant firm and if the plant is located in a country different from the country of the parent company's global ultimate owner.

Formally, we regress E-PF *gain* and E-TFP *gain* on a vector of firm-specific variables, by means of OLS over the pooled sample:

$$Y_{i,s} = \delta_1 + \mathbf{d}_2 \mathbf{X}_{i,s} + \varepsilon_{i,s}, \tag{12}$$

with $Y_{i,s}$ being alternatively E-PF *gain* and E-TFP *gain*, 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.

[insert Table 6 about here]

We find correlations that are broadly consistent with our interpretation of E-PF *gain* and E-TFP *gain* reflecting technological and managerial environmental productivity. Plants closer to the technological frontier (i.e. E-PF *gain* is lower) belong to larger, international, and multi-plant companies. Plants belonging to an international owner and to companies with higher intangibles intensity more commonly show improved environmental management. Finally, listed firms and older firms have, respectively, lower E-PF *gain* and lower E-TFP *gain* (but these effects show weaker statistical significance after accounting for country fixed effects).[13]

[13] 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

Overall, these correlations are consistent with previous evidence about firm characteristics, technological upgrades and TFP, outside the environmental context. A suggestive, yet speculative interpretation of this finding is that environmental friendly technologies and management practices are driven by international exposure and broader access to external funding and to higher quality inputs. Hence, firms may tend to adopt them 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.

6 Conclusions

Industrial economists have shown extensively, over a large number of industries and time periods, that productivity asymmetries across firms are wide and persistent also when increasing the level of disaggregation (Bartelsman and Doms, 2000; Syverson, 2011). This has stimulated finer and finer methodological strategies, aimed at exploring the intra-industry heterogeneity in productivity and its causes (Disney *et al.*, 2003; Dosi *et al.*, 2016; Battisti *et al.*, 2020; Amoroso and Martino, 2020; Dosi *et al.*, 2021; de Roux *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 output and non-marketed environmental inputs? And to which extent can these differences be interpreted as differences in technology? 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

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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".

In this paper we propose an innovative methodology to decompose environmental productivity into a technological (group-specific) and a managerial (plant-specific) 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 technologies available in the sector and on the degree of technological sharing across plants), 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).

Our analysis yields the general result that cross-plants differentials in environmental management are non-negligible, the technological component of environmental productivity dispersion being qualitatively important in many sectors. We find that more than two-thirds of regulated plants in our European sample uses sub-optimal technologies, whereas adopting the locally optimal technology would lead on average to a 75% increase in output, emissions being equal. Interestingly, the distribution of both technology and managerial differences tends to be associated with several firm characteristics, with managerial 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 credit-constrained firms (De Haas *et al.*, 2021).[14]

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 plant level.

Second, the paper shows that there is a great variability across regulated plants (even within countries and sectors) in technological and managerial environmental quality, with many capped plants adopting sub-optimal technologies and others adopting optimal (or close to optimal) technologies together with environmentally inefficient managerial practices. We show that these asymmetries tend to be systematic, with international firms having both better technologies and better management than the average. This 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 (including technology management) diffusion as a primary target for environmentally oriented industrial policy. Our findings also lend support to the adoption of flexible policies, that combine technology standards with market-based regulations inducing each firm to curb its emissions by means of what arguably is the most effective strategy given the nature of its own environmental efficiency bug. Related to this, we also find that what is an optimal technology, in terms of envi-

[14] A broader body of study on (non-environmental) TFP 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).

ronmental productivity, depends on the plant's level of emissions. Hence, one-size-fits-all technology standards may be inappropriate for some plants and less effective, on average, than emission-contingent technology prescriptions.

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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-PF$_1$	E-PF$_2$	E-PF$_3$	E-PF$_4$	E-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.

Table 3: Technology-sector distributions (%).

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-TFP dispersion conditional on technology.

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

Table 5: Potential gains from eliminating emission intensity dispersion.

Sector	E-PF *gain*	E-TFP *gain*	*Total gain*
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)

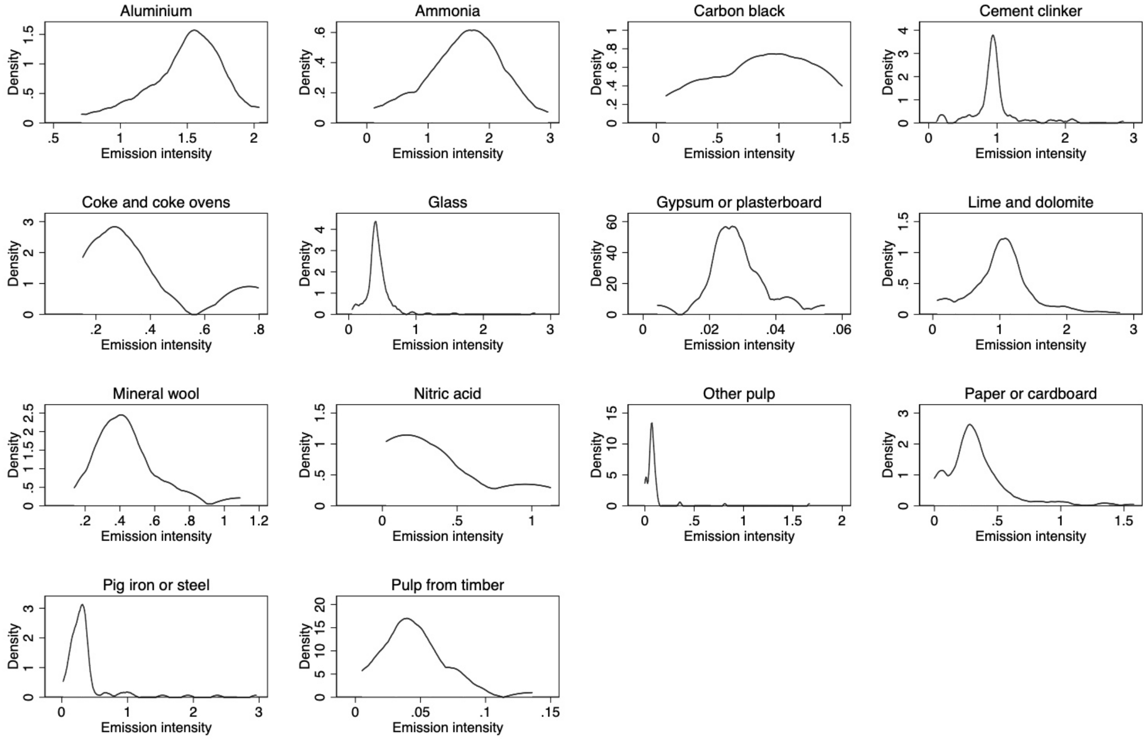
Note. E-PF *gain* quantifies the increase in Q that would be obtained by moving to the counterfactual scenario where all firms adopt E-PF*, expressed as a ratio with respect to the observed (i.e. actual) levels of Q. E-TFP *gain* quantifies the increase in Q that would be obtained by moving to the counterfactual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

Table 6: E-PF *gain*, E-TFP *gain* and parent firms' characteristics.

	[1] E-PF *gain*	[2] E-TFP *gain*	[3] E-PF *gain*	[4] E-TFP *gain*
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-plant 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

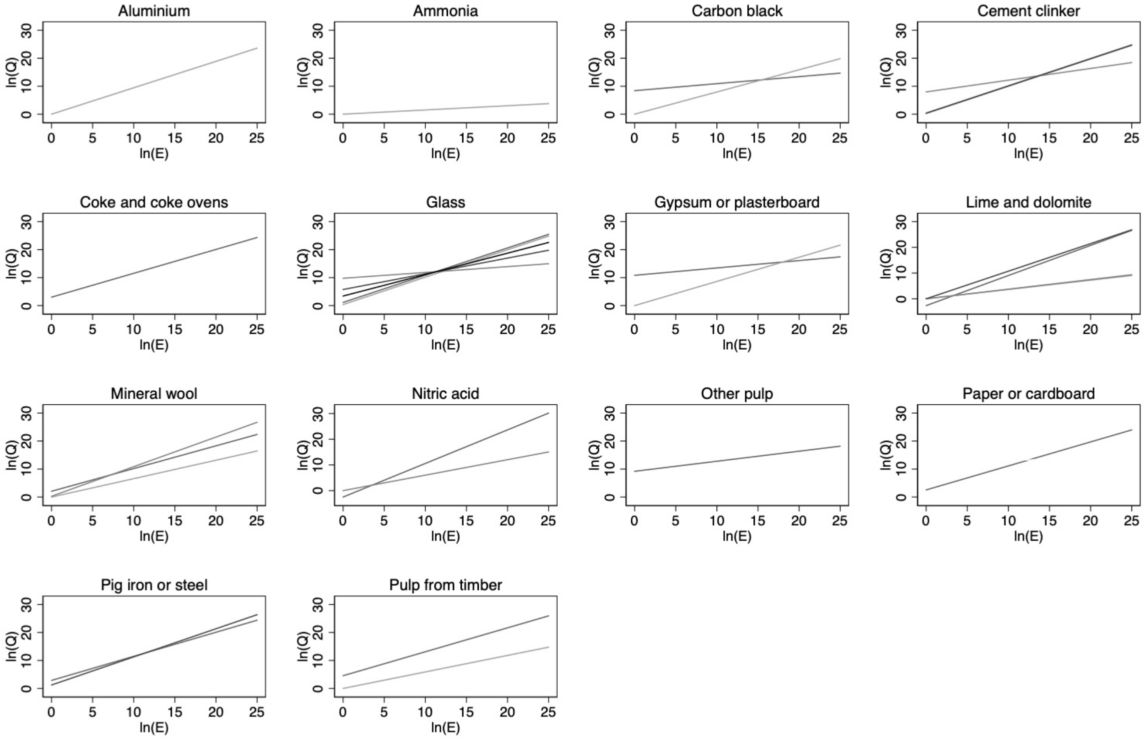
Statistical significance: * =10%, ** =5%, *** =1%. Standard errors are in parentheses. Plant level OLS regressions. All sectors pooled. Sectors with $\tilde{\mathcal{T}} = 1$ are omitted from the E-PF *gain* regressions.

Figure 1: Distribution of emission intensity within sectors.



Note. Emission intensity is measured at the plant-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)).

Figure 2: Estimated environmental-production functions.



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.

Appendix

A.1. Additional tables and figures

Table 7: 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

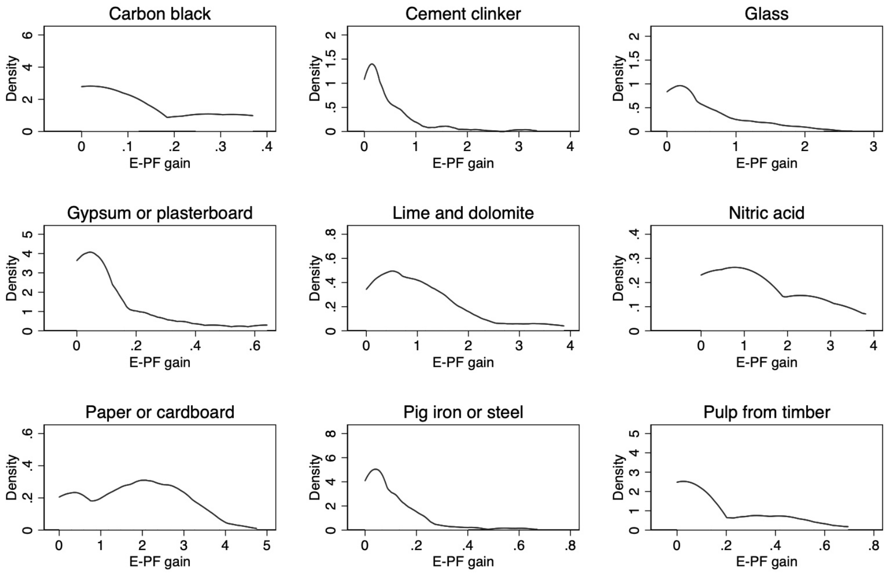
Note. The carbon leakage exposure factor - CLEF ($\lambda_{s,t}$) is constant 1 or decreasing at a predetermined rate depending on the carbon leakage status of the sector. The cross-sectoral correction factor - CSCF (ϑ_t) ensures that total allocation remains below the maximum amount pursuant to article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

Table 8: 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

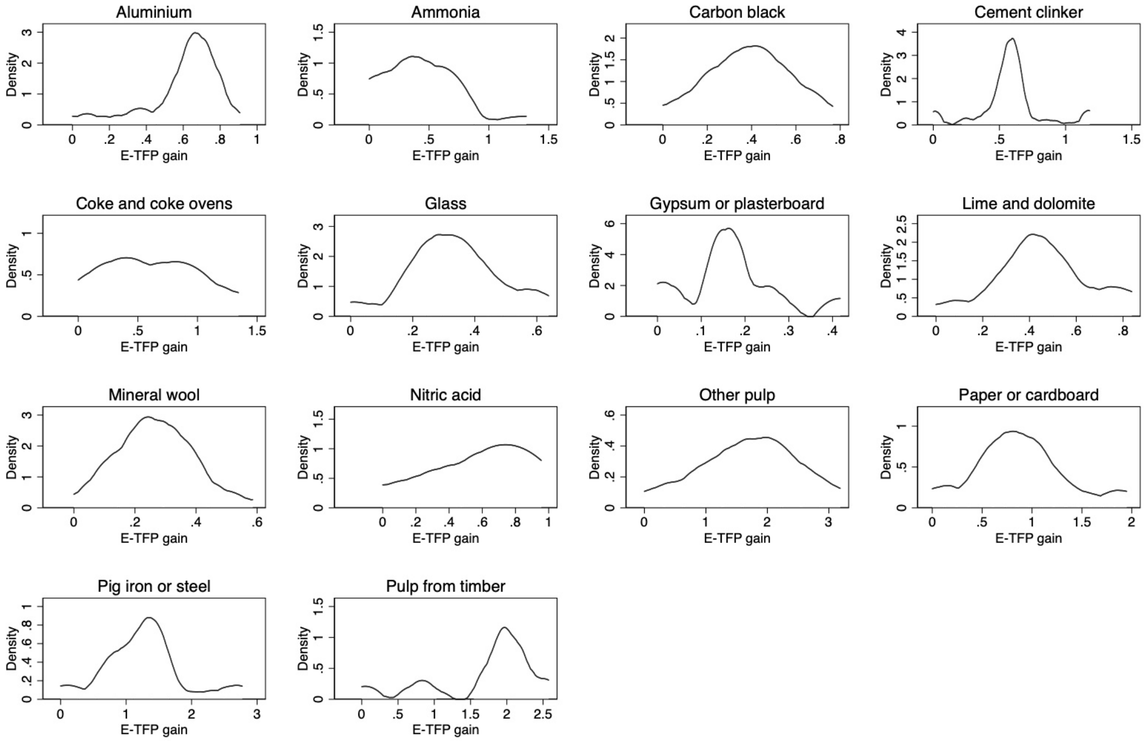
Note. Product-specific benchmark emission intensities are listed in European Commission (2011) according to a classification that is more granular than the EU-OHA sectors classification. We cross-walked the two classifications using product-sector description matching: (i) 1-to-1 match is obtained when 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.

Figure 3: Distribution of E-PF *gain* within sectors.



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

Figure 4: Distribution of E-TFP *gain* within sectors.



Note. E-TFP *gain* quantifies the increase in Q_i that would be obtained by a plant by having the same E-TFP 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.

A.2. Endogeneity bias

It is well known since Marschak and Andrews (1944) that, if the firm has knowledge of its productivity parameter when making input choices, these choices will likely be dependent on the productivity itself. This is the so-called "simultaneity problem". In our framework, this equals to say that both $\alpha_{i,\tau}$ and $\{\alpha_\tau, \beta_\tau\}$ in Eq. (3) may be biased due to the fact that, while the true productivity terms are unobserved by the econometrician, they are 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 production function estimation.

Starting with Olley and Pakes (1996), various approaches have been proposed to tackle the simultaneity problem (see Ackerberg *et al.* (2007) and De Loecker and Syverson (2021) for reviews on this). A traditional approach is the one relying on an instrumental variable (IV), i.e. a variable that is correlated with the endogenous explanatory variables but does not directly enter the production function and is uncorrelated with the productivity term. The economics of production suggests input prices as natural instruments. To use the price of the inputs as 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 plants through "grandfathering" at the start of the EU ETS in 2005. Following Directive 2003/87/EC on greenhouse gas emissions trading, in 2005 each plant eligible to enter the EU ETS was provided with a number of allowances allocated free of charge based on the plant's historical (predetermined) emissions. Fortunately for us, the number of allowances freely allocated was both unexpected by polluters and independent of their current production behaviour. Moreover, economic theory suggests that pollution permits influence output only through their effect on emissions.

Denote the number of allowances allocated through "grandfathering" in 2005 as $A_{i,2005}$. We integrate our mixture model estimation of Eq. (3) with the following first stage:

$$E_i = \gamma_1 + \gamma_2 A_{i,2005} + \epsilon_i \tag{13}$$

The predicted values from Eq. (13) are used in the production function estimation. Then, we run again all the steps of our counterfactual analysis and obtain E-PF *gain* and E-TFP *gain* as recomputed based on the IV estimation of the productivity terms. The OLS correlation between E_i and $A_{i,2005}$ over the pooled sample is reported in Table 9 and the final results of the counterfactual exercise in Table 10.[15]

[insert Table 9 about here]

[insert Table 10 about here]

The results are qualitatively similar to those obtained without accounting for endogeneity. In particular, we observe that the total gain in environmental productivity due to removing both sources of productivity 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 plant data from the aluminium sector, plus we find other four sectors with only one technology. This explains why the technological dimension of productivity dispersion is relatively lower (and the managerial dispersion relatively higher) than in the baseline estimates.

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

Figure 5, finally, shows that the differences, respectively, between the baseline E-PF *gain* and the IV-based E-PF *gain* and between the baseline E-TFP *gain* and the IV-based E-TFP *gain* are not systematic.

[insert Figure 5 about here]

Table 9: 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	23883.36	0.000

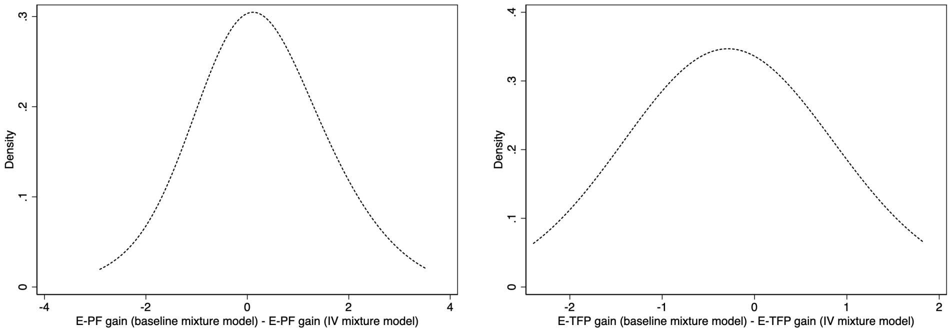
Note. Statistical significance: * =10%, ** =5%, *** =1%. Standard errors are in parentheses. Plant level OLS regression. All sectors pooled.

Table 10: Potential output gains: IV estimates.

SECTOR	E-PF *gain*	E-TFP *gain*	*Total gain*
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* 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-TFP *gain* quantifies the increase in Q that would be obtained by moving to the counterfactual scenario where all firms have E-TFP*, the technology in use being equal, expressed as a ratio with respect to the observed (i.e. actual) levels of Q. *Total gain* is the sum of E-PF *gain* plus E-TFP *gain*. E-PF *gain*, E-TFP *gain* and *Total gain* 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. (3). Aluminium is omitted due to non convergence in the mixture model estimation.

Figure 5: Difference between baseline and IV-based E-PF *gain* and E-TFP *gain*.



Note. E-PF *gain* 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-TFP *gain* quantifies the increase in Q that would be obtained by moving to the counterfactual scenario where all firms have E-TFP*, 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* obtained by means of the baseline mixture model and E-PF *gain* obtained by means of the IV mixture model; (right-hand panel) the distribution of the difference between E-TFP *gain* obtained by means of the baseline mixture model and E-TFP *gain* obtained by means of the IV mixture model. Pooled sample.

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