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Digging into Environmental Productivity: Is It All about Technology?

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Abstract

We propose a mixture model approach to decompose environmental productivity into a managerial and a technological dimension, and to identify locally optimal technologies. For a large sample of plants covered by the EU Emission Trading System, we find that the average output gains, emissions being equal, that plants could reach by adopting the locally optimal technology and the best managerial practices available in the sector are 162% and 53% respectively, with significant cross-plant and cross-sector differentials. This data-driven decomposition delivers important policy insights, as it helps predicting larger reductions in emission intensity from flexible policies than from one-size-fits-all technology-based standards.

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

JEL classification: D24, L60, Q54, Q55

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1 Introduction

It is largely documented that in many OECD countries emission intensity of manufacturing sectors has been falling over the last decades (e.g., Najjar and Cherniwchan (2020)). Looking at the plant-level, recent empirical evidence shows that the decline of emission intensity is driven primarily by a within-product increase in environmental productivity (i.e. output per unit of emission) rather than changes in the composition of products produced (Shapiro and Walker, 2018). Yet, environmental productivity dispersion remains substantial even within narrowly defined industries. In particular, it is still poorly understood whether cross-plant differentials 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 implications for environmental policy, because it would help evaluating the potential gains of technology-oriented policies in comparison with policies aimed at diffusing improved environmental management.[1]

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

[1]Technology-oriented 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). Policies aimed at diffusing improved environmental management are typically more nuanced. One example of policies of this type is the support for adopting environmental management systems, such as those certified with the ISO 14001 (a standard released by the International Organization for Standardization that sets out the requirements for more efficient use of resources and reduction of waste).

(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). We restrict our study to the EU ETS Phase 3, which means the period 2013-2019. This allows us to recover physical output levels for each plant from the inverse permit allocation rule, thereby affording additional granularity relative to the existing literature.[2] Then, our analysis proceeds in two main stages.

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 firm 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).[3] Brought to our data, this exercise delivers a number of technologies ranging from one (in mineral wool manufacturing) to six (in the production of aluminium), with most sectors having more than two technologies. 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.[4] We find that the probability weighted share of firms adopting the frontier technology is about 25% 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).

Next, 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 which the plant continues to be attached to the probability of adopting each technology as estimated in the first

[2]Firm level data of regulated units under the EU ETS have been used by recent literature, particularly for examining the effects of cap-and-trade programs on the development and adoption of environmental technologies, as measured by low-carbon patenting and R&D spending (e.g., Calel and Dechezlepretre (2016), Calel (2020)).

[3]This empirical mixture method is similar in spirit to the one developed by Battisti *et al.* (2020) in a more classical TFP context.

[4]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)).

stage but shows the E-TFP of the top 5% performers in each technology group. 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 162%, while using the best managerial practices would entail an output gain of about 53%, emissions being equal. On average, the total gain from technology upgrades when both sources of productivity dispersion are eliminated is about 216%. Behind these averages, we also document that the growth margins of environmental productivity differ substantially both across sectors and across plants within sectors.

Taken together, our results urge to reconsider one-size-fits-all direct regulations as the preferred way for improving environmental productivity. Based on this conclusion, ambitious public policy plans to address climate change, such as the Green New Deal in the US and the European Green Deal, arguably would be required to complement prescriptive regulations (e.g., technology standards) with sets of indirect policies allowing for flexible firm reactions. This would leave each firm free to choose undertaking technology or managerial improvements depending on the nature of its own environmental productivity gap—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 present the data. In Section 3 we explain in detail the steps of our methodology. In Section 4 we provide a quantification of the technological and the managerial components of environmental productivity dispersion. Section 5 concludes by explaining the policy relevance of our analysis.

2 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.

For the years 2013-2019 we are able to retrieve the plant-level output from the inverse allowance allocation rule employed in the EU ETS Phase 3. Allocation of allowances is 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. Hence, a plant's emission intensity can be calculated as:

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

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

The distribution of $e_{i,t,s}$ within sectors is illustrated in Figure 1.[6] As the figure shows, there are significant emission intensity differentials across European plants both across and within sectors. 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.

3 Environmental production functions estimation

The environmental-production function of plant i is:

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

[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 13269 installation-year observations. Details on CLEF, CSCF and benchmark emission intensities are provided in the online Appendix.

[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 firm i's output with respect to the fitted output of the firms 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 firm-specific managerial component of environmental productivity. In Equation (3), the subscripts s and t are suppressed for ease of reading, as our estimation is carried out on pooled within-sector sub-samples (hence, hereafter the unit i refers to an installation-year observation in sector s).

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_τ^2, weighted by the ex-ante probabilities π_τ of belonging to group τ, i.e.:

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

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.

Table 1 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 technologies ranging from one (in mineral wool manufacturing) to six (in the production of aluminium), with most sectors having more than two technologies. Interestingly enough, while the emission coefficient β_τ is generally lower than one, a number of technologies have β_τ greater than one. All the technology-specific E-PFs are plotted in Figure 2.

[insert Table 1 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 $\ln(\hat{Q}_{i,\tau^*})|E_i > \ln(\hat{Q}_{i,\tau})|E_i \ \forall \tau \neq \tau^*$. Note that τ^* is "locally" optimal because conditional on E_i, i.e. two or more E-PFs may intersect at some point of the distribution of E_i. Indeed, as shown in Figure 2, in all sectors where $\tilde{\mathcal{T}} > 1$, 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-year observation 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, the within-sector share of plants adopting

[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 $\mathcal{T} > 7$ in any sector. Detailed results of this BIC-based selection procedure are relegated in the online Appendix.

technology τ^* ranges from 6.87% in the aluminium industry to 54.80% in the production of pulp from timber, it being 24.98% on average.[8] 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.

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.

$$\alpha_{i,\tau^*} = \ln(Q_i) - \tilde{p}_{i,\tau^*} \ln(\hat{Q}_{i,\tau^*}) \qquad \text{and} \qquad \alpha_{i,\tau\neq\tau^*} = \ln(Q_i) - \sum_{\tau=1}^{\tilde{\mathcal{T}}} \tilde{p}_{i,\tau} \ln(\hat{Q}_{i,\tau}) \ \forall \tau \neq \tau^*, \tag{9}$$

and compare their estimated variances. Sectoral figures are in Table 2. We find that $\widehat{\mathrm{Var}}(\alpha_{i,\tau^*}) > \widehat{\mathrm{Var}}(\alpha_{i,\tau\neq\tau^*})$ only in the production of pig iron, steel and other pulp, while the opposite holds in all the other sectors, thereby revealing that the use of the frontier technology may help to reduce cross-plant differentials in managerial environmental performance. This may be consistent with very recent research showing that environmental management quality correlates positively with green investments at the firm level (De Haas *et al.*, 2021).

[insert Table 2 about here]

4 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

[8] A complete table of technology-sector distributions is provided in the online Appendix.

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 3 reports the sectoral averages of E-PF *gain*, E-TFP *gain* and *Total gain*.[10]

[insert Table 3 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 162%, while using the best managerial practices would entail an output gain of about 53%, emissions being equal. When both sources of productivity dispersion are eliminated, the total gain in environmental productivity is about 216%.

On the other side, we also find significant heterogeneity in the relative size of these gains across sectors. In the production of aluminium, paper and cardboard, the technology dimension

[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 online Appendix.

of environmental productivity dispersion is quantitatively the most significant, accounting by more than two-thirds of the total dispersion. Productions of pulp from timber and other pulp are associated with much larger idiosyncratic differences. Clearly, in the mineral wool industry, where only one E-PF was found in our mixture model estimation, productivity gains would come only from eliminating E-TFP dispersion.

5 Conclusions

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 however the most important dimension in most sectors. We find that more than 75% of plants uses sub-optimal technologies, whilst adopting the locally optimal technology would lead on average to a 162% increase in output, emissions being equal. Interestingly, the cross-plant variance of the managerial dimension of environmental productivity is 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). 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 plants (even within countries and sectors) in both technological and managerial environmental quality, with many plants adopting optimal (or close to optimal) technologies together with environmentally harmful managerial practices. This lends support to flexible policy measures 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 environmental 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.

Future research may take advantage from the methodology presented here to conduct policy impact evaluation over a broad range of regulatory issues as well as to explore the relationship between firm (or even plant) characteristics and both technology and managerial practices, e.g. along the line initiated by Bloom *et al.* (2010) and Martin *et al.* (2012).

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Table 1: 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$_5$	E-PF$_6$
Aluminium	$\beta_1 = 1.050$	$\beta_2 = 0.104$	$\beta_3 = 0.969$	$\beta_4 = 0.054$	$\beta_5 = 0.210$	$\beta_6 = 0.841$
	$\alpha_1 = -0.936$	$\alpha_2 = 8.836$	$\alpha_3 = 0.000$	$\alpha_4 = 11.367$	$\alpha_5 = 9.557$	$\alpha_6 = 1.528$
Ammonia	$\beta_1 = 0.677$	$\beta_2 = 0.014$	$\beta_3 = 0.384$	$\beta_4 = 1.074$		
	$\alpha_1 = 3.449$	$\alpha_2 = 12.601$	$\alpha_3 = 7.952$	$\alpha_4 = -1.673$		
Carbon black	$\beta_1 = 0.694$	$\beta_2 = 0.296$	$\beta_3 = 0.119$	$\beta_4 = 0.216$	$\beta_5 = 0.467$	
	$\alpha_1 = 3.449$	$\alpha_2 = 7.618$	$\alpha_3 = 9.771$	$\alpha_4 = 9.341$	$\alpha_5 = 6.386$	
Cement clinker	$\beta_1 = 1.114$	$\beta_2 = 0.577$	$\beta_3 = 0.015$	$\beta_4 = 0.200$	$\beta_5 = 0.857$	
	$\alpha_1 = -1.190$	$\alpha_2 = 6.053$	$\alpha_3 = 13.227$	$\alpha_4 = 10.969$	$\alpha_5 = 0.000$	
Coke and coke ovens	$\beta_1 = 0.488$	$\beta_2 = 1.010$	$\beta_3 = 0.496$	$\beta_4 = 1.030$		
	$\alpha_1 = 7.206$	$\alpha_2 = 0.000$	$\alpha_3 = 0.000$	$\alpha_4 = 0.000$		
Glass	$\beta_1 = 1.060$	$\beta_2 = 0.714$	$\beta_3 = 0.387$	$\beta_4 = 0.915$		
	$\alpha_1 = 0.177$	$\alpha_2 = 0.000$	$\alpha_3 = 6.994$	$\alpha_4 = 0.000$		
Gypsum or plasterboard	$\beta_1 = 0.938$	$\beta_2 = 0.851$				
	$\alpha_1 = 4.020$	$\alpha_2 = 0.000$				
Lime and dolomite	$\beta_1 = 1.154$	$\beta_2 = 0.276$	$\beta_3 = 0.833$			
	$\alpha_1 = -1.846$	$\alpha_2 = 8.096$	$\alpha_3 = 0.000$			
Mineral wool	$\beta_1 = 1.039$					
	$\alpha_1 = 0.348$					
Nitric acid	$\beta_1 = 1.359$	$\beta_2 = 0.491$	$\beta_3 = 0.695$			
	$\alpha_1 = -3.081$	$\alpha_2 = 0.000$	$\alpha_3 = 4.924$			
Other pulp	$\beta_1 = 1.069$	$\beta_2 = 0.643$	$\beta_3 = 0.282$			
	$\alpha_1 = 1.954$	$\alpha_2 = 6.072$	$\alpha_3 = 10.689$			
Paper or cardboard	$\beta_1 = 0.875$	$\beta_2 = 0.041$	$\beta_3 = 0.309$			
	$\alpha_1 = 2.290$	$\alpha_2 = 12.789$	$\alpha_3 = 9.034$			
Pig iron or steel	$\beta_1 = 0.683$	$\beta_2 = 0.751$	$\beta_3 = 1.059$			
	$\alpha_1 = 4.747$	$\alpha_2 = 4.086$	$\alpha_3 = 0.602$			
Pulp from timber	$\beta_1 = 0.822$	$\beta_2 = 0.013$				
	$\alpha_1 = 4.980$	$\alpha_2 = 13.163$				

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 2: E-TFP dispersion conditional on technology.

SECTOR	$\widehat{\text{Var}}(\alpha_{i,\tau^*})$	$\widehat{\text{Var}}(\alpha_{i,\tau\neq\tau^*})$
Aluminium	0.001	0.008
Ammonia	0.001	0.010
Carbon black	0.001	0.053
Cement clinker	0.002	0.024
Coke and coke ovens	0.002	0.006
Glass	0.013	0.018
Gypsum or plasterboard	0.001	0.023
Lime and dolomite	0.016	0.018
Mineral wool	0.119	–
Nitric acid	0.002	0.074
Other pulp	0.785	0.462
Paper or cardboard	0.006	0.107
Pig iron or steel	0.158	0.128
Pulp from timber	0.208	0.496

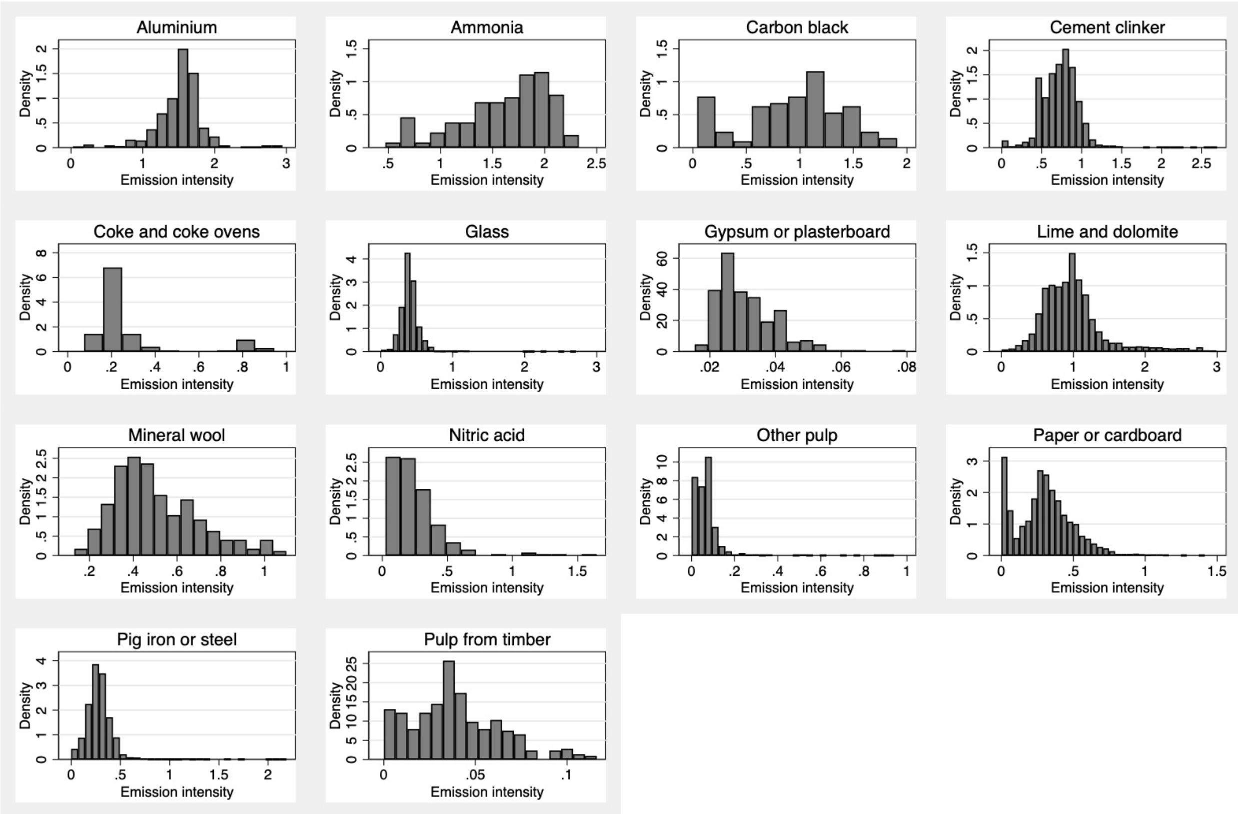
Note. In mineral wool manufacturing, only one technology is identified.

Table 3: Potential gains from eliminating emission intensity dispersion.

SECTOR	E-PF *gain*	E-TFP *gain*	*Total gain*
Aluminium	1.267	0.181	1.448
	(1.028)	(0.094)	(1.037)
Ammonia	0.206	0.224	0.430
	(0.292)	(0.104)	(0.305)
Carbon black	0.571	0.405	0.977
	(0.454)	(0.244)	(0.535)
Cement clinker	0.584	0.315	0.900
	(0.963)	(0.170)	(0.989)
Coke and coke ovens	0.285	0.178	0.464
	(0.478)	(0.094)	(0.487)
Glass	0.209	0.314	0.523
	(0.261)	(0.157)	(0.330)
Gypsum or plasterboard	0.209	0.314	0.446
	(0.111)	(0.159)	(0.245)
Lime and dolomite	0.377	0.386	0.764
	(0.666)	(0.193)	(0.720)
Mineral wool	0.000	0.619	0.619
	(0.000)	(0.345)	(0.345)
Nitric acid	0.830	0.535	1.365
	(0.746)	(0.279)	(0.845)
Other pulp	0.246	1.197	1.444
	(0.350)	(0.481)	(0.651)
Paper or cardboard	5.648	0.550	6.199
	(4.179)	(0.329)	(4.076)
Pig iron or steel	0.222	0.648	0.871
	(0.304)	(0.305)	(0.464)
Pulp from timber	0.450	2.199	2.649
	(0.787)	(0.812)	(1.076)
All sectors pooled	1.626	0.535	2.162
	(3.086)	(0.812)	(3.089)

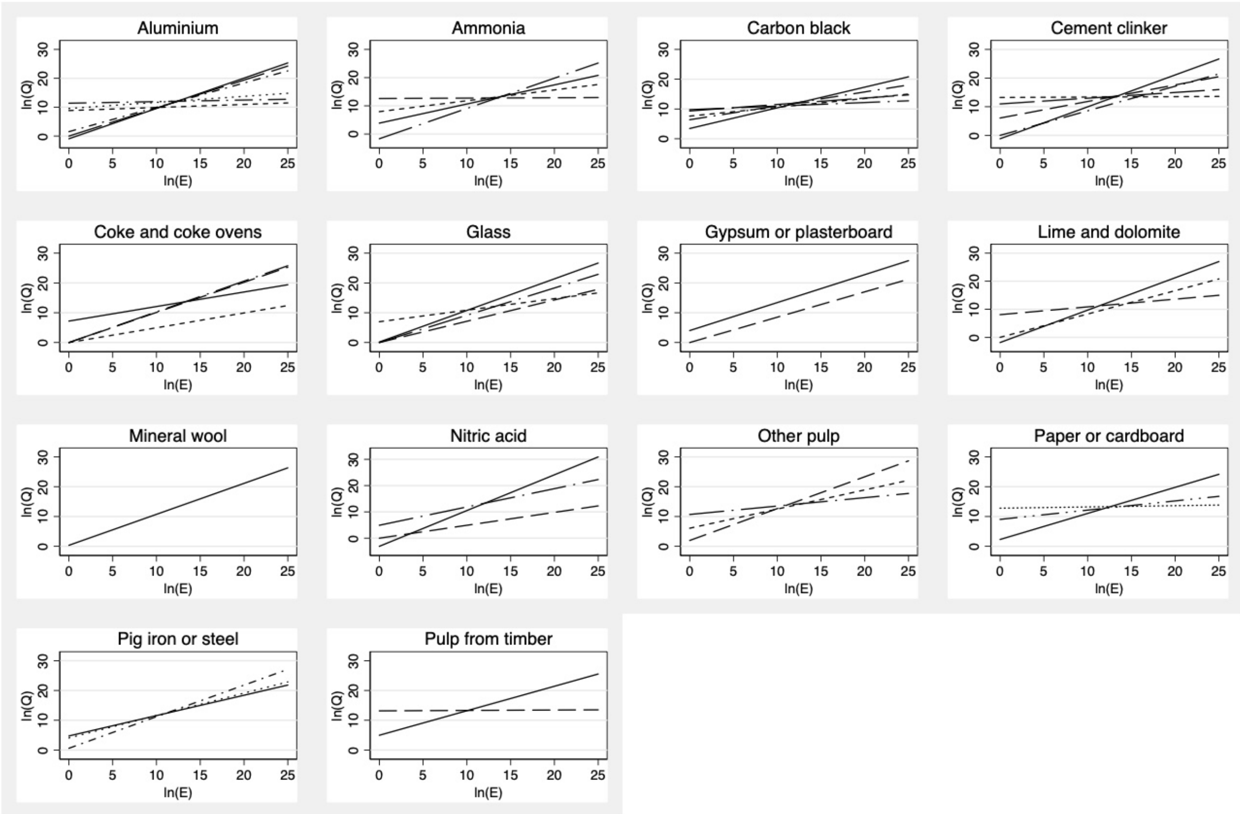
Note. E-PF *gain* quantifies the increase in Q that would be obtained by moving to the counterfactual scenario where all firms adopt E-PF*, expressed as a ratio with respect to the observed (i.e. actual) levels of Q. E-TFP *gain* quantifies the increase in Q that would be obtained by moving to the counterfactual 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.

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. Details of the BIC-bases procedure for selecting the optimal number of clusters is relegated to the online Appendix.

Digging into Environmental Productivity: Is It All about Technology?

– SUPPLEMENTARY MATERIAL –

(for online publication)

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A.1. Robustness checks

A.1.1. Unobservables longitudinal variations in output levels

We obtained the output level of plant i from the inverse allocation rule, i.e. as:

$$Q_{i,s} = \frac{A_{i,t,s}}{\tilde{e}_s \, \lambda_{s,t} \, \vartheta_t} \tag{12}$$

In (12), $Q_{i,s}$ is the baseline output level of plant i in sector s calculated as the median of the activity level in 2005-2008. As such, $Q_{i,s}$ is time invariant. At the same time, however, total emissions of installation i may vary over time. Hence, in our model, any variation in total emissions causes variations in emission intensity. Nevertheless, there may be instances in which variations in emissions reflect variations in output (e.g. when a product demand shock occurs): yet, contemporaneous output is unobservable in our data and these cases are erroneously treated as changes in environmental productivity (i.e. changes in the probability $\tilde{p}_{i,\tau}$ of adopting a given technology or changes in E-TFP or both).

Here, we run a simple exercise to verify to which extent this problem may affect our results. First, we inspect graphically the frequency and the magnitude of 1-year changes in $\tilde{p}_{i,\tau}$. Figure 6 displays the histograms of the 1-year changes in the plant's probability of adopting each technology, by pooling all sectors together. It is easy to see that such changes are zero (or very close to it) for most observations. This means that the probability of each plant to adopt each technology remains substantially unchanged over the considered period. Second, we re-compute E-PF *gain*, E-TFP *gain* and $Total\ gain$ by using $\bar{p}_{i,\tau}$ as a probability weight, instead of $\tilde{p}_{i,\tau}$, with $\bar{p}_{i,\tau}$ being the average of $\tilde{p}_{i,\tau}$ over the period 2013-2019 for plant i. In this way, we eliminate longitudinal variations in technology adoption at the plant-level. The results are collected in Table 8. Reassuringly, we observe only minimal differences from our benchmark analysis and our general findings remain qualitatively unchanged. From this exercise, we conclude that both the technology clustering and the E-TFP measure obtained by means of our mixture model strategy are substantially driven by cross-sectional heterogeneity, rather than by longitudinal variations in plant-level emission intensities. Even if our empirical strategy may confound variations in production levels with variations in environmental productivity, any noise resulting from this appears to have negligible consequences on our statistical decomposition.

A.2. Additional tables and figures

Table 4: 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 5: 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 6: 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	670.742	-104.525	-130.812	-193.796	-143.187	-224.298	n.c.	n.c.	n.c.	n.c.	-224.298	6
Ammonia	-45.878	-54.595	-70.272	-72.851	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	-72.851	4
Carbon black	176.651	160.579	152.609	144.884	141.626	n.c.	n.c.	n.c.	n.c.	n.c.	141.626	5
Cement clinker	2841.490	1016.442	696.918	695.031	684.139	689.609	n.c.	n.c.	n.c.	n.c.	684.139	5
Coke and coke ovens	160.599	49.388	0.053	-10.724	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	-10.724	4
Glass	1849.974	905.895	846.479	670.979	734.192	750.994	745.737	n.c.	n.c.	n.c.	670.979	4
Gypsum or plasterboard	74.240	59.010	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	59.010	2
Lime and dolomite	2382.981	1940.071	1477.744	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	1477.744	3
Mineral wool	276.941	288.327	306.014	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	276.941	1
Nitric acid	550.510	473.126	426.584	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	426.584	3
Other pulp	2889.779	2734.133	2687.130	2699.199	2695.510	n.c.	n.c.	n.c.	n.c.	n.c.	2687.130	3
Paper or cardboard	9981.363	6929.672	6901.560	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	6901.560	3
Pig iron or steel	3243.590	1983.146	1942.582	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	1942.582	3
Pulp from timber	1009.078	788.306	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	706.908	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 7: Technology-sector distributions (%).

Sector	$\tau = \tau_1$	$\tau = \tau_2$	$\tau = \tau_3$	$\tau = \tau_4$	$\tau = \tau_5$	$\tau = \tau_6$	$\tau = \tau^*$
Aluminium	29.32	1.76	54.67	1.13	3.32	9.77	6.87
Ammonia	68.65	4.95	11.66	14.72			11.01
Carbon black	69.22	2.14	5.88	3.36	19.37		7.77
Cement clinker	32.26	10.19	0.84	4.91	51.78		10.21
Coke and coke ovens	12.29	48.56	19.55	19.58			15.74
Glass	30.82	23.87	2.88	42.41			24.55
Gypsum or plasterboard	67.58	32.41					32.41
Lime and dolomite	39.19	7.98	52.81				36.93
Mineral wool	100.00						100.00
Nitric acid	14.42	21.39	64.17				19.48
Other pulp	38.58	18.32	43.09				41.90
Paper or cardboard	68.78	7.95	23.25				8.68
Pig iron or steel	8.64	17.95	73.39				20.21
Pulp from timber	94.28	5.71					54.80
All sectors pooled							24.98
All sectors pooled (w/out mineral wool)							23.33

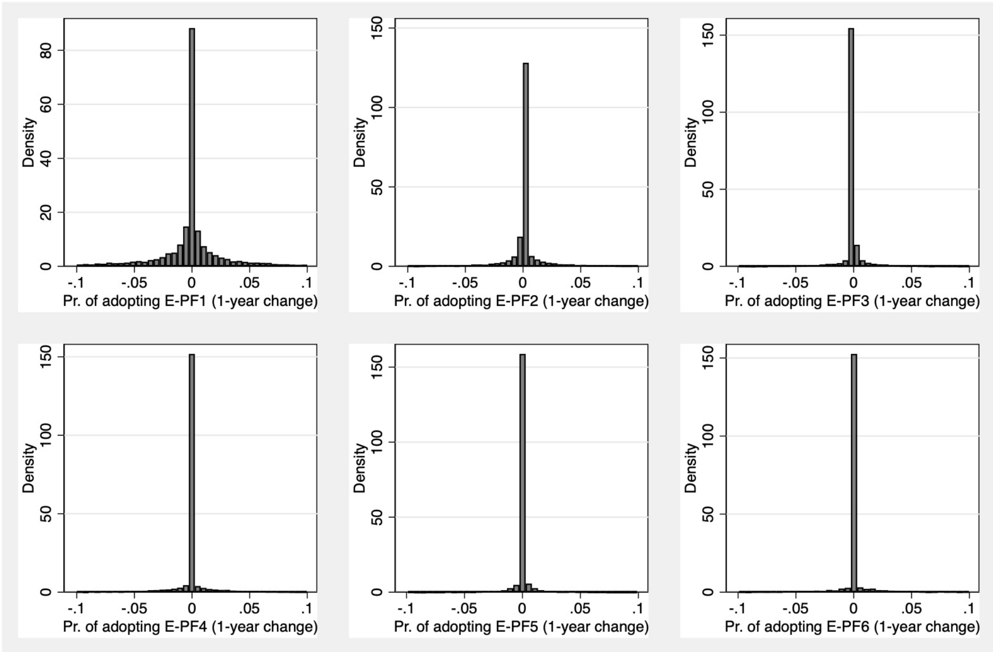
Note. Entries are within-sector shares (%) of plant-year observations across technology clusters, weighted by the probability $\tilde{p}_{i,\tau}$ of belonging to each cluster. The locally optimal technology cluster is τ^*.

Table 8: Potential output gains under time invariant clustering.

Sector	E-PF *gain*	E-TFP *gain*	*Total gain*
Aluminium	1.278	0.173	1.452
	(1.028)	(0.247)	(1.046)
Ammonia	0.222	0.224	0.446
	(0.278)	(0.160)	(0.314)
Carbon black	0.572	0.403	0.975
	(0.429)	(0.308)	(0.550)
Cement clinker	0.627	0.295	0.922
	(0.985)	(0.334)	(0.995)
Coke and coke ovens	0.460	0.178	0.639
	(0.469)	(0.127)	(0.493)
Glass	0.224	0.308	0.533
	(0.263)	(0.279)	(0.383)
Gypsum or plasterboard	0.220	0.225	0.446
	(0.091)	(0.208)	(0.270)
Lime and dolomite	0.407	0.378	0.785
	(0.658)	(0.294)	(0.741)
Mineral wool	0.000	0.613	0.613
	(0.000)	(0.381)	(0.381)
Nitric acid	0.854	0.526	1.380
	(0.729)	(0.364)	(0.891)
Other pulp	0.658	1.268	1.926
	(0.633)	(0.983)	(1.214)
Paper or cardboard	5.671	0.547	6.218
	(4.020)	(0.533)	(3.914)
Pig iron or steel	0.232	0.661	0.894
	(0.291)	(0.645)	(0.720)
Pulp from timber	0.463	2.170	2.633
	(0.775)	(0.939)	(1.133)
All sectors pooled	1.680	0.535	2.216
	(3.027)	(0.632)	(3.055)

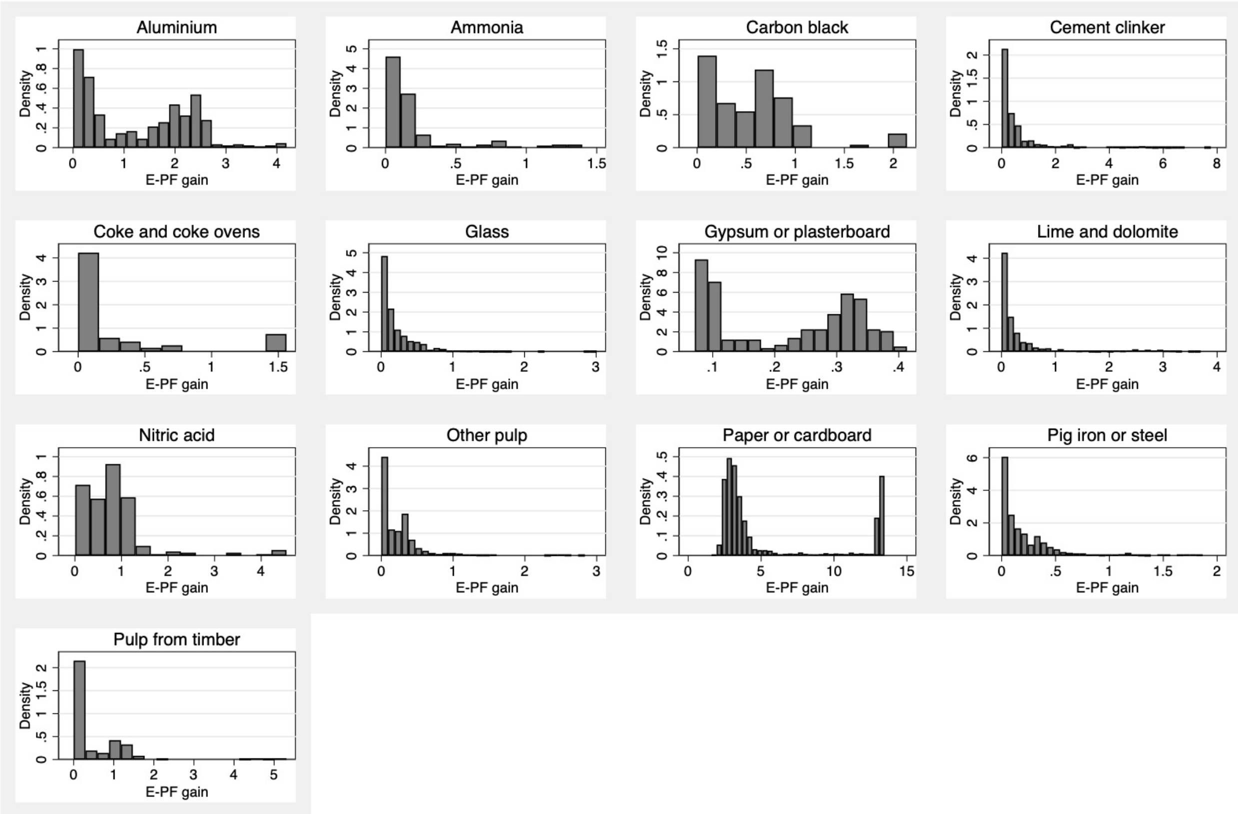
Note. E-PF *gain* quantifies the increase in Q that would be obtained by moving to the counterfactual scenario where all firms adopt E-PF*, expressed as a ratio with respect to the observed (i.e. actual) levels of Q. E-TFP *gain* quantifies the increase in Q that would be obtained by moving to the counterfactual 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. All the gains reported in the table are computed by using $\bar{p}_{i,\tau}$ as a probability weight, instead of $\tilde{p}_{i,\tau}$, with $\bar{p}_{i,\tau}$ being the average of $\tilde{p}_{i,\tau}$ over the period 2013-2019 for installation i.

Figure 3: 1-year changes in the probability of adopting each E-PF (all sectors pooled).



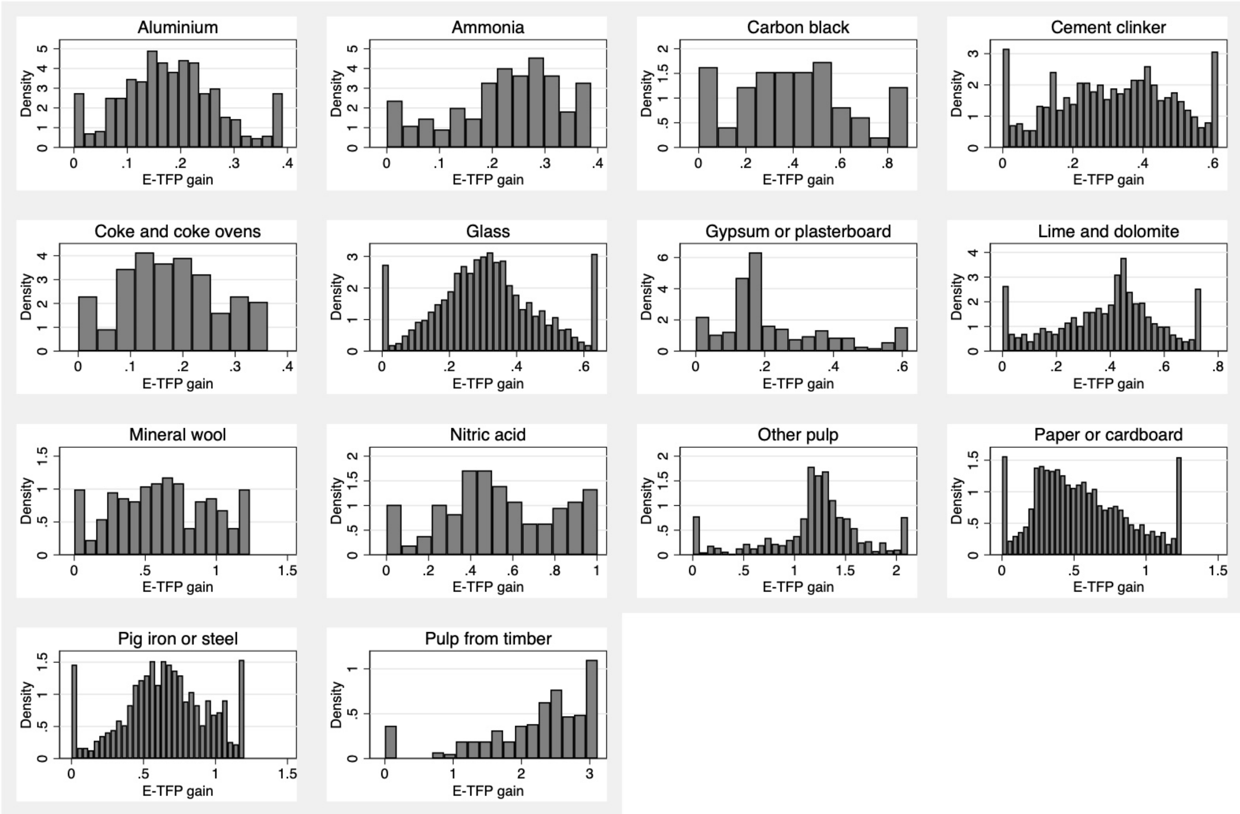
Note. Histograms of plant-level 1-year changes in the probability $\tilde{p}_{i,\tau}$ of adopting each E-PF (all sectors pooled).

Figure 4: 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$_{\tau^*}$, expressed as a ratio with respect to the observed (i.e. actual) levels of Q_i. Production of mineral wool is omitted because only one technology cluster was identified in this sector.

Figure 5: 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.