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Abstract

This paper attempts to estimate the impact of pollution abatement investments on the production technology of firms by pursuing two new directions. First, we take advantage of recent econometric developments in productivity and efficiency analysis and compare the results obtained with two complementary approaches: parametric stochastic frontier analysis and conditional nonparametric frontier analysis. Second, we focus not only on the average effect but also on its heterogeneity across firms and over time and search for potential nonlinearities. We provide new results suggesting that such an effect is heterogeneous both within firms and over time and indicating that the effect of pollution abatement investments on the production process is not monotonic. These results have relevant implications both for modeling and for the purposes of advice on environmentally friendly policy.

JEL classification: C14, C23, D24, Q50.

Keywords: Pollution abatement investments, technology, stochastic frontier analysis, conditional nonparametric frontier analysis, generalized product kernels, generalized local polynomial kernel regression.

1 Introduction

Pollution clearly appears to be an undesirable output of production. Because producing cleanly is more expensive than polluting, environmental regulation may be necessary in order to incite firms to make investments devoted to pollution reduction and to pursue a sustainable process of economic development. A standard view among economists is that environmental regulation aiming to reduce pollution is a detrimental factor for firms' competitiveness and productivity (Jorgenson and Wilcoxen, 1990). Since the early 1990s, however, this view has been challenged by numerous economists. In particular, Porter (1991) and Porter and Van der Linde (1995) argued that more stringent but properly designed environmental regulations do not inevitably hamper firms' competitiveness but could enhance it. This new paradigm has become known as the 'Porter hypothesis'. Since then, such a hypothesis has received much attention. It was initially criticized for its lack of an underlying theory (Palmer *et al.*, 1995) and for being inconsistent with the empirical evidence (Jaffe *et al.*, 1995), while today a more solid theory exists (André, 2015) but also rather mixed empirical evidence, suggesting that *"further research is clearly needed in this area"* (Ambec *et al.*, 2013, p. 10).

This paper aims to contribute to the literature by pursuing two new directions.

First, within a methodological perspective, we aim to assess the effect of pollution abatement investments on the production technology of firms by adopting methods that have been recently developed by the econometric literature on productivity and efficiency analysis and that leave room for the consideration of external factors of production. External variables are generally defined as variables that cannot, at least totally, be controlled by the producer but may have an influence in the production process (Bădin et al., 2012). The available measures of firms' efforts to reduce pollution, such as pollution abatement investments, can be seen as these kinds of variables, as they are expected to be stimulated by environmental regulation and, at the same time, to have some kind of effect on the production technology of firms.

A second novel aspect of this paper is its empirical and policy-oriented perspective. Specifically, we focus not only on the average effect but also on its variability across firms and over time and search for potential nonlinearities. These aspects have been recognized as extremely relevant by the theoretical literature and have important implications, but until now, they have been neglected by the existing empirical literature. Indeed, as already pointed out by previous works (Ambec et al., 2013), the controversy over the Porter hypothesis centers on the likelihood that the regulatory costs may be fully offset or not. The critics say that although some anecdotal empirical evidence in the direction suggested by Porter could be found, a complete offset should be seen as the exception. Porter and van der Linde also admit that such a complete offset does not always occur. Moreover, the linearity and monotonicity of the relation can also be questioned, as *"it is not reasonable to assume that the effect of environmental regulation is monotonic"* (André, 2015, p. 29) since it could be that taking advantage of regulation will become more difficult if the stringency of environmental regulation will increase too much.

In order to model pollution abatement investments as external factors of production and to address the above issues, two complementary approaches are adopted in this paper: parametric stochastic frontier analysis (SFA) and conditional nonparametric frontier analysis (CNFA). They present relative advantages and drawbacks; comparing their results may be useful to provide a more nuanced and thorough picture of the effect of pollution abatement investments on the production technology of firms. SFA has the relative advantage of having a well-developed statistical theory which allows for statistical inference. Therefore, using SFA we can test alternative specifications as well as different hypotheses on efficiency. We can focus our attention on input elasticities, on their heterogeneity across firms and on all the other estimated parameters of the production frontier and get information on scale economies, efficiency, etc. Conversely, CNFA has the relative advantage over SFA that it does not make any assumptions, either about specific parametric functional form for the production frontier or about distributional assumptions on the noise and inefficiency component, and may be useful to detect complex nonlinear relations. At the same time, however, this flexibility comes at a price since CNFA does not allow the estimation of some key elements of production econometrics (such as input elasticities, scale economies, etc.) and inference is less straightforward than in SFA.

More specifically, concerning SFA, the most common approaches in the literature model the impact of external factors either on the structure of the technology or on technical efficiency (Coelli et al., 1999). We follow and extend these trends and consider alternative models to include pollution abatement investments in the production process and then use the Vuong (1989) test in order to select the most likely one. When switching to CNFA, we use a two-step approach similar to Mastromarco and Simar (2015) where at the first stage conditional nonparametric efficiency measures are obtained and are used as exploratory tools (Cazals et al., 2002; Daraio and Simar, 2005; Bădin et al., 2012) and, at the second stage they are regressed nonparametrically over pollution abatement capital. We follow recent advances in nonparametric regression and depart from previous works since, at the second stage, we avoid ad hoc determination of the local polynomial order by using the Generalized Local Polynomial Kernel Regression approach recently proposed by Hall and Racine (2015). This allows – via delete-one cross-validation – the joint determination of the polynomial order and bandwidth and can have a relevant impact on the quality of the resulting approximation.

In summary, to the best of our knowledge, this is the first work estimating the effect of pollution abatement investments on the production technology of firms using methods that model pollution abatement investments as external factors of production and, at the same time, focusing on some aspects – such as heterogeneity and nonlinearity – that have been shown to be relevant by the theoretical literature and have important implications for firms and society as a whole in terms of advice on environmentally friendly policy.

The present paper is organized as follows. Section 2 gives a brief review of the related literature. Section 3 presents the econometric methodologies while the description of the data and some descriptive statistics are provided in section 4. Section 5 details the results and section 6 concludes.

2 Literature

In this section, we present the general ideas and the different versions of the Porter hypothesis. We also briefly review the theoretical literature, specifically highlighting the economic mechanisms allowing for a possible positive relation between pollution abatement investments and firm-level productivity. For a more exhaustive discussion on both theory and empirics, the reader is referred to the recent surveys by Ambec et al. (2013) and André (2015).

According to a standard view among economists, at least until the 1990s, pollution abatement effort due to environmental regulation may be beneficial in terms of environmental performance but would negatively affect firms' economic performances since it forces them to allocate the production inputs to pollution reduction, pushing them away from optimal production choices and thus inducing technological and allocative inefficiency.

Since the early 1990s, however, this traditional paradigm has been challenged by what has become known as the 'Porter hypothesis' (Porter, 1991; Porter and Van der Linde, 1995). Porter and Van der Linde (1995, p. 98) suggest that *"Strict environmental regulation can trigger innovation (broadly defined) that may partially or more than fully offset the traditional costs of regulation"*.

Since then, the Porter hypothesis has attracted a great deal of attention, theoretically as well as empirically. However, a difficulty that arises when addressing such a hypothesis is clarifying its interpretation, as the Porter hypothesis is not a hypothesis in a statistical sense but it represents a general idea illustrated with real-life examples and, at least in its original formulation, lacked an underlying theory (Palmer et al., 1995). Jaffe and Palmer (1997) help in the interpretation of the Porter hypothesis by distinguishing between the 'weak', 'narrow' and 'strong' versions of such a hypothesis. According to the weak version, environmental regulation may stimulate innovation, while the narrow version argues that certain types of environmental regulation, but not all, spur innovation. This idea that regulation can stimulate innovation is based on the concept of induced innovation and goes back to Hicks (1932). It is generally accepted and has been validated by many previous studies, even those specifically about environmental regulation. The core of the controversy lies in the strong version, which argues that *in many cases* this innovation more than offsets the regulatory costs, ultimately enhancing firms' competitiveness and economic performances. From a theoretical point of view, after some initial criticisms (Palmer et al., 1995), the literature has provided alternative explanations supporting the strong version, such as firms' behaviors departing from the assumption of profit maximization (Ambec and Barla, 2007), market failure (André et al., 2009), organization failure (Ambec and Barla, 2002), and knowledge spillovers (Mohr, 2002).

It should also be noted that while Porter and van der Linde claim that firms become *"more competitive"*, the concept of competitiveness is quite general and allows for alternative measurements. As a consequence, the above-mentioned theoretical works have considered alternatives measures of competitiveness such as cost reduction, increased profits or higher market shares. At the same time, however, empirical research has focused on the estimation of production functions or productivity equations. Somewhat more closely related to this empirical literature, Mohr (2002) emphasizes productivity increases and justifies the Porter hypothesis by adopting a general equilibrium model where a key role is played by external economies and in particular the nature of knowledge as a public good. According to such a model, firms' output benefits from knowledge spillovers. The amount of this common knowledge is equal to the cumulative production experience of all firms using the same technology. Thus, a specific firm will switch to a new (greener) technology only if enough other firms have done it first. This is because, even if new and greener technology will be, ceteris paribus, more productive, at least initially there is much more accumulated experience in the old technology than in the new one and, as a consequence, the productivity of the new technology will be lower than that of the old one. Environmental regulation can thus solve the coordination problem, inciting firms to adopt the greener technology, which will increase the global stock of knowledge of the new technology, and ultimately lead to an improvement in the level of productivity of those firms.

3 Methodology

There is a huge body of empirical literature testing the strong version of the Porter hypothesis, but it provides rather mixed empirical evidence (Ambec *et al.*, 2013). This literature focuses on the estimation of production functions or productivity equations augmented with some measures of pollution abatement efforts. We follow the stream of the literature using a direct measure of the expenditures or investments engaged by the firms (see e.g., Shadbegian et al., 2005) and estimate value-added production frontiers where the pollution abatement efforts are measured with the stock of capital devoted to pollution reduction (a detailed description of the data is in section 4).

The methodology we use departs from previous studies in that it is inspired by recent developments in the econometric literature on productivity and efficiency analysis that allow the consideration of external factors of production. SFA and CNFA provide useful frameworks for dealing with this issue. This section shows how these two approaches can be used to model the impact of pollution abatement capital on the production process.

3.1 Stochastic frontier analysis

The most common approaches in the SFA literature model the impact of external factors either on the structure of the technology or on technical efficiency (Kumbhakar and Lovell, 2000). We follow and extend these trends and consider two alternative models to include pollution abatement capital in the production process.

Input model

In a first model, which we label as the *input model*, we assume that pollution abatement capital influences the production process itself, or, put differently, enters the production function, $F(.)$, as an additional factor of production in the stochastic production frontier model

$$Y_{it} = F(t, K_{it}, L_{it}, Z_{it})\tau_{it}w_{it}. \tag{1}$$

The output of a firm i at time t, Y_{it}, is thus assumed to be determined not only by the levels of usual inputs, i.e. labor input, L_{it}, and physical capital, K_{it}, but also by pollution abatement capital, Z_{it}. The time trend t captures technological change over time and we do not assume Hicks-neutrality. The w_{it}, which are assumed to be independent and identically distributed random errors, capture the stochastic nature of the production frontier. τ_{it} denotes technical efficiency with $0 < \tau_{it} \leq 1$ and $\tau_{it} = 1$ when the firm produces on the frontier.

The stochastic production frontier model in Eq. (1) is parameterized using a translog specification achieving local flexibility (also called Diewert flexibility, see e.g., Fuss *et al.,* 1978) and outperforming other Diewert-flexible forms (Guilkey *et al.,* 1983):

$$\begin{aligned} y_{it} \;\; = \;\; & \alpha + \beta_\tau t + \beta_k k_{it} + \beta_l l_{it} + \beta_z z_{it} + \gamma_\tau \frac{t^2}{2} + \gamma_k \frac{k_{it}^2}{2} + \gamma_l \frac{l_{it}^2}{2} + \gamma_z \frac{z_{it}^2}{2} + \\ & + \delta_{\tau k} t k_{it} + \delta_{\tau l} t l_{it} + \delta_{\tau z} t z_{it} + \delta_{kl} k_{it} l_{it} + \delta_{kz} k_{it} z_{it} + \delta_{lz} l_{it} z_{it} - u_{it} + v_{it} \end{aligned} \tag{2}$$

where lower case letters indicate variables in natural logs, i.e. $y_{it} = \ln(Y_{it})$, and so on. It is worth noting that this specification is more general than the one chosen by Coelli *et al.* (1999) which restricts the effect of external factors only to the shape of the technology by imposing $\gamma_z = \delta_{\tau z} = \delta_{kz} = \delta_{lz} = 0$ in Eq. (2). Put differently, we do not exclude the case where pollution abatement capital affects the technology of the firms as an input under the control of the firm manager choosing the optimal level of pollution abatement investments given some external constraints (such as environmental regulation) and within its maximization program. The error term in Eq. (2) is composed of two components, the two-sided noise component $v_{it} = \ln(w_{it})$ and the non-negative technical inefficiency component $u_{it} = -\ln(\tau_{it})$. The noise component, v_{it}, is assumed to be independently and identically distributed as $N(0, \sigma_v^2)$ and distributed independently of u_{it}. The technical inefficiency component, u_{it}, is assumed to be time-varying. Two different assumptions about the distribution of this component can then be made. First, we can assume that the technical inefficiency component is of the multiplicative form:

$$u_{it} = \ell(t, T) \times u_i$$

where u_i is distributed as $N(\mu, \sigma_u^2)$ truncated at zero and $\ell(t, T)$ is written as

$$\ell(t, T) = \exp(\sum_{t=2}^{T} \gamma_t d_t) \tag{3}$$

where d_t denote year dummies.[1] Hereafter we will refer to this specification as *multiplicative*.

A second specification for the inefficiency component, which we label as *additive*, builds on Battese and Coelli (1995) and Coelli *et al.* (1999) with u_{it} distributed as $N\left(\mu_{it}, \sigma_u^2\right)$ truncated at zero and

$$\mu_{it} = \mu + \sum_{t=2}^{T} \gamma_t d_t \tag{4}$$

The two specifications of the technical inefficiency component differ in the way they model time-varying inefficiency. In the multiplicative specification, the underlying truncated normal variable u_i is scaled by the exponential function of time. The inefficiency component in this specification varies in a systematic way with respect to time. Greene (2005) defines this specification of the inefficiency component as "time-dependent" rather than as time-variant. The other inefficiency specification is a pooled model where the time variation of inefficiency depends on the way time affects the mean of the truncated distributed variable u_{it}.

Efficiency model

In the input model, pollution abatement capital is assumed to influence production directly, by affecting the structure of the production frontier relative to which the efficiency of firms is estimated. An alternative model associating variation in efficiency with variation in pollution abatement capital can be also considered. In this model, which is labeled as the *efficiency model*, Eq. (1) becomes

$$Y_{it} = F(t, K_{it}, L_{it})\tau_{it}(Z_{it})w_{it}. \tag{5}$$

where we assume now that pollution abatement capital, Z_{it}, influences production, Y_{it}, indirectly, through its effect on technical efficiency, τ_{it}. The stochastic production frontier model in Eq. (5) is parameterized using a flexible translog specification as

$$y_{it} = \alpha + \beta_\tau t + \beta_k k_{it} + \beta_l l_{it} + \gamma_\tau \frac{t^2}{2} + \gamma_k \frac{k_{it}^2}{2} + \gamma_l \frac{l_{it}^2}{2} + \delta_{\tau k} t k_{it} + \delta_{\tau l} t l_{it} + \delta_{kl} k_{it} l_{it} - u_{it} + v_{it} \tag{6}$$

Here too, the error term in Eq. (6) is composed of two components, the two-sided noise component $v_{it} = \ln(w_{it})$ and the non-negative technical inefficiency component $u_{it} = -\ln(\tau_{it})$. We assume again that the noise component, v_{it}, is independently and identically distributed as $N(0, \sigma_v^2)$ and distributed independently of u_{it}. Two alternative specifications of the distribution of the technical inefficiency component, u_{it}, are considered, a *multiplicative* one and an *additive* one, as for the input model. But now, the multiplicative form of the inefficiency component in the multiplicative model becomes

$$u_{it} = \ell(t, T, Z_{it}) \times u_i,$$

[1] By construction, a constant term in Eq. (3) capturing the effect of the first year cannot be identified simultaneously with the mean of the truncated normal so the value of the constant term is set to zero.

where u_i is distributed as $N(\mu, \sigma_u^2)$ truncated at zero and $\ell(t, T, Z_{it})$ is written as

$$\ell(t, T, Z_{it}) = \exp(\sum_{t=2}^{T} \gamma_t d_t + \theta Z_{it}), \tag{7}$$

Meanwhile, the assumptions in the additive model become u_{it} distributed as $N(\mu_{it}, \sigma_u^2)$ truncated at zero and

$$\mu_{it} = \mu + \sum_{t=2}^{T} \gamma_t d_t + \theta Z_{it} \tag{8}$$

To sum up, we have four parametric models: input model with multiplicative inefficiency component, input model with additive inefficiency component, efficiency model with multiplicative inefficiency component, and efficiency model with additive inefficiency component. These four models are estimated by maximum likelihood. Since they are non nested, in order to choose the preferred specification, we perform the modified likelihood-ratio test proposed by Vuong (1989) to compare non-nested models.

3.2 Conditional Nonparametric Frontier Analysis

The parametric approach allows the estimation of some key elements of production econometrics, such as elasticities, scale economies, etc. However, even if a flexible form is used to represent the production technology, such an approach might suffer from misspecification problems due to imposing a specific functional form on the production process and assuming known statistical distributions on the errors terms.[2] The use of nonparametric methods serves to relax these restrictive parametric assumptions, even if these methods do not allow the estimation of parameters for economic interpretation. Moreover, using recent developments in nonparametric frontier literature (Cazals et al., 2002; Daraio and Simar, 2005 and 2007; Bădin et al., 2012, Mastromarco and Simar, 2015), it is possible to disentangle the potential effects of conditioning variables (in our case, pollution abatement capital) to identify effects on the boundary (the shape of the frontier) and effects on the distribution of the inefficiencies in a full nonparametric setup.

First step: Exploratory tools

We follow Cazals et al. (2002), Daraio and Simar (2005, 2007) and, mainly, Mastromarco and Simar (2015) who introduce the time dimension into the conditional frontier model. The production process generates random variables (X, Y, Z) in an appropriate probability space, where $X \in \mathbb{R}_+^p$ denotes the vector of inputs, $Y \in \mathbb{R}_+^q$ denotes the vector of outputs, and $Z \in \mathbb{R}_+^r$ denotes the vector of variables describing external factors, i.e. factors that may influence the production process and the efficiency pattern (in our case, pollution abatement capital and time). As suggested by Mastromarco and Simar (2015), time can be handled as a Z variable.

[2]For instance, Guilkey et al. (1983) have shown that the translog approximation outperforms other Diewert-flexible forms such as the generalized Leontief and the generalized Cobb-Douglas, but also provides a reliable approximation only if the complexity of the underlying technology is not too high.

For each time period t, the attainable set $\Psi^z \subset R_+^{p+q}$ is defined as the support of the conditional probability[3]

$$H_{X,Y|Z}(x,y|z) = \text{Prob}\left(X \leq x, Y \geq y \mid Z = z\right).$$

The function $H_{X,Y|Z}\left(x,y|z\right)$ is simply the probability for a firm operating at level (x,y) to be dominated by firms facing the same external conditions z. Accordingly, the conditional output-oriented technical efficiency of a production plan $(x,y) \in \Psi^z$, i.e. facing external conditions z, can be defined as (Daraio and Simar, 2005)

$$\tau\left(x,y|z\right) = \sup\left\{\tau|(x,\tau y) \in \Psi^z\right\} = \sup\{\tau|S_{Y|X,Z}(\tau y|x,z) > 0\}.$$

where $S_{Y|X,Z}(y|x,z) = \text{Prob}(Y \geq y|X \leq x, Z = z)$ is the (nonstandard) conditional survival function of Y, nonstandard because the condition on $X \leq x$ and not $X = x$.[4]

We also calculate partial frontiers, introduced by Daouia and Simar (2007), enabling us to obtain results that are robust to some extreme observations. Conditional (unconditional) output-oriented robust order-α quantile efficiency measures are defined for any $\alpha \in (0,1)$ as:[5]

$$\tau_\alpha(x,y|z) = \sup\{\tau|S_{Y|X,Z}(\tau y|x,z) > 1-\alpha\}$$

As stated in Bădin et al. (2012), the effect of external factors on the shape of the frontier can be investigated by considering the ratios of conditional $(\tau(x,y|z))$ to unconditional $(\tau(x,y))$ efficiency measures, which are measures relative to the full frontier of respectively, the conditional and the unconditional attainable production sets:

$$R_O(x,y|z) = \frac{\tau(x,y|z)}{\tau(x,y)}. \tag{9}$$

By construction, $R_O(x,y|z) \leq 1$, whatever the triplet (x,y,z). In turn, the effect of external factors on the distribution of technical efficiencies can be investigated using the ratios of conditional to unconditional output-oriented robust order-α quantile efficiency measures for

[3]From now on, we use capital letters for random variables and lowercase letters for the values these random variables take.

[4]Let $H_{X,Y}(x,y)$ denote the unconditional probability of being dominated. Then we have

$$H_{X,Y}\left(x,y\right) \quad = \quad \int_Z H_{X,Y|Z}\left(x,y|z\right) f_Z(z) dz$$

having support Ψ, the unconditional attainable production set which is defined as $\Psi = \bigcup_{z\in Z} \Psi^z$. It is clear that, by construction, $\Psi^Z \subset \Psi$. Unconditional output-oriented technical efficiency of a production plan (x,y), can then be defined as

$$\tau(x,y) = \sup\{\tau|(x,\tau y) \in \Psi\} = \sup\{\tau|S_{Y|X}(\tau y|x) > 0\},$$

where $S_{Y|X}(y|x) = \text{Prob}(Y \geq y|X \leq x)$ is the unconditional survival function of Y given that $X \leq x$. Here too, it is clear that, by construction, $\tau\left(x,y|z\right) \leq \tau(x,y)$.

[5]The unconditional measures are: $\tau_\alpha(x,y) = \sup\{\tau|S_{Y|X}(\tau y|x) > 1-\alpha\}$.

different values of α, i.e

$$R_{O,\alpha}(x,y|z) = \frac{\tau_\alpha(x,y|z)}{\tau_\alpha(x,y)}. \tag{10}$$

Here the ratios $R_{O,\alpha}(x,y|z)$ can be either ≤ 1 or ≥ 1. But as $\alpha \to 1$, $R_{O,\alpha}(x,y|z) \to R_O(x,y|z)$

For the output orientation, when the ratios (9) are globally increasing with an external factor, this indicates a favorable effect on the production process, and the external factor can be considered as a freely available input. Indeed, the value of $\tau(x,y|z)$ is much smaller (greater efficiency) than $\tau(x,y)$ for small values of the factor than for large values of it. In our case with Z as pollution abatement capital, this may be explained by the fact that firms facing small values of the external factor do not take advantage of the favorable environment, and when the value of the external factor increases, they benefit more and more from the environment. On the contrary, when the ratios (9) are globally decreasing with the external factor, there is an unfavorable effect of this factor on the production process. The external factor is then acting as an unavoidable output. In this situation $\tau(x,y|z)$ will be much smaller than $\tau(x,y)$ for large values of the external factor.

As explained in Bădin et al. (2012), the full frontier ratios (9) indicate only the effects of external factors on the shape of the frontier, whereas with the partial frontier ratios (10), these effects may combine effects on the shape of the frontier and effects on the conditional distribution of the inefficiencies. For our purpose of analyzing the impact of Z on the distribution of efficiencies, we are interested in the median, by choosing $\alpha = 0.50$. If the effect on partial frontier ratios is similar to the one shown with the ratios with full frontier, we can conclude that we have a shift of the frontier while keeping the same distribution of the efficiencies when the external factor changes. If the effect with the median ($\alpha = 0.5$) is greater than for the full frontier, this indicates that in addition to an effect on the shape of the frontier, we also have an effect on the distribution of the efficiencies.[6]

Nevertheless, the conclusions of the analysis of ratios should be taken with caution and regarded only as exploratory. In fact, they are valid if the choice of inputs is independent of the external factors. If not, the analysis of the ratios as a function of the external factors should be conducted for fixed levels of the inputs. The interpretations given above as to the impact of the external factors, which depends on the shape of the relation between the ratios and the factors, remain valid, but for a fixed vector of inputs.

Second step: Nonparametric regression of the conditional efficiency scores

To go further into the analysis of the impact of external factors, Bădin et al. (2012) propose to analyze the average behavior of $\tau(x,y|z)$ as a function of z, in order to capture the main effect of the external factors on these conditional measures. We thus regress, in the second stage, the conditional efficiency scores $\tau(x,y|z)$ on pollution abatement capital and time. This is motivated by the fact that the so-called 'separability condition' discussed in Simar and Wilson (2007) likely does not hold. Indeed, under such a condition, neither time nor pollution abatement capital influences the shape of the attainable set. But this appears very restrictive

[6]The full frontier corresponds to an extreme quantile, i.e. the maximum achievable output. See Figure 10, in Bădin et al., (2012) for a detailed explanation of the different possible scenarii.

and an unlikely event since if technical change occurs, the frontier of the attainable set will change with time. In such a case, as suggested by Bădin et al. (2012), in the second stage it is meaningful to analyze the average behavior of the conditional efficiency scores $\tau(x, y|z)$ - rather than the unconditional ones $\tau(x, y)$ - as a function of the external factors. Here too, the conditional efficiency scores $\tau(x, y|z)$ may also vary with both z and x. But now, we want to capture the marginal effect of Z on the efficiency scores, so it is legitimate to analyze the regression model $\mathbb{E}\left(\tau(x, y|z)|Z = z\right)$ as a function of z. Therefore, we focus attention on the following nonparametric regression function:

$$\tau(x, y|z) = m(z) + \varepsilon$$

where $m(.)$ is un unknown smooth function to be estimated and ε is the usual error term such that $\mathbb{E}(\varepsilon|Z = z) = 0$.

To estimate this model, we follow recent advances in nonparametric regression and depart from the above-mentioned works which estimate location-scale regression models with the local constant approach, for two reasons. First and most important, we use the Generalized Local Polynomial Kernel Regression approach recently proposed by Hall and Racine (2015) rather than adopting the local constant approach. This allows – via delete-one cross-validation – the joint determination of the polynomial order and bandwidth, avoiding the ad hoc determination of the polynomial order, which is the standard practice in applied works. As also stressed by Hall and Racine (2015), the order of the polynomial can have a relevant impact on the quality of the resulting approximation, while the appropriate order will in general depend on the underlying and unknown DGP. Such a method allows improvements in both finite sample efficiency and in the rate of convergence, which for some common DGPs, is equal to the parametric rate for the Oracle estimator, $O(n^{-1/2})$. Second, we do not use the location-scale regression model, i.e. when the error term can be expressed as $\varepsilon = \sigma(z)\varepsilon$. While in some cases it could be of interest to adopt this model, in our specific case we do not focus on the scale effect, $\mathbb{V}\left(\tau(x, y|z)|Z = z\right)$, whereas the location effect, $\mathbb{E}\left(\tau(x, y|z)|Z = z\right)$, is of primary interest. If one wants to estimate the variance function $\sigma^2(z)$ in the location-scale model, one simply needs to regress nonparametrically the square of the residuals on the external factors.

4 Data

We build a new and rich firm-level panel data set concerning the French food processing industries and covering a relatively long period (1993-2007), the French food processing industry being particularly relevant for such a kind of analysis. The food industry is relevant in terms of size, representing a large proportion of manufacturing in France (about 550,000 employees in 2011, i.e. 18% of manufacturing employment). It is also relevant because it is one of the most polluting sectors with respect to several indicators, especially concerning the effects of total final consumption of the produced goods (European Environmental Agency, 2006). Moreover, in 2007, the food processing industry was found to be the third biggest spender on pollution abatement investments in France (€167 million), only exceeded by the energy (€437 million) and chemicals, rubbers and plastics (€204 million) industries.

Data for the French food processing industries on pollution abatement investments are collected annually in a survey conducted by the French ministry of Agriculture, called *Enquête Annuelle sur les Dépenses pour Protéger l'Environnement* (ANTIPOL), since the early 1990s. To our knowledge, this paper represents the first attempt to use this survey for academic purposes. The ANTIPOL survey provides information on pollution abatement investments defined as *"the purchase of buildings, land, machinery or equipment to limit the pollution generated by production activity and internal activities or the purchase of external services improving the knowledge to reduce pollution"*. Next, the pollution abatement capital stock at firm level is built using the perpetual inventory method with a depreciation rate of 15%. This is a standard rate adopted in the literature for investments in pollution abatement (Aiken *et al.*, 2009).

The *Enquête Annuelle d'Entreprise* (EAE) is an annual firm-level survey covering almost all firms with 20 or more employees, conducted by the French National Institute for Statistics. This survey provides a measurement for output, i.e. value-added, deflated by its annual industry price index, and for the usual inputs, i.e. labor measured by the number of employees expressed in annual full-time equivalent workers, and capital measured by the amount of fixed assets, deflated by the annual price index for capital goods.

The two data sets are merged, finally resulting in an unbalanced panel data set composed of 8391 observations and 1130 firms covering the period 1993-2007. Table 1 presents some descriptive statistics for the variables used to estimate the production function: value added, labor (number of workers), physical capital stock, and pollution abatement capital stock.[7] This table shows that average pollution abatement capital stock is about one-fiftieth of average physical capital stock. Also note that a fraction of firms has never invested to reduce pollution, the corresponding stock of capital presents many zeros (18.21% of the total number of observations), but all the explanatory variables are expressed in logarithms when using a translog specification. To include all the observations for the variable Z, we follow Battese (1997), and set $z \equiv \ln(Z + D)$ where $D = 1$ if $Z = 0$, and $D = 0$ if $Z > 0$, as explanatory variable instead of $\ln(Z)$ which is not defined when $D = 1$. Battese (1997) also introduces the variable D as a shifter of the constant term. As we introduce sectoral dummies to capture unobserved heterogeneity across sectors, we do not introduce the dummy D. Indeed, sectoral dummies can capture the effect of omitted variables that explain the heterogeneity of pollution abatement investment behaviors across sectors, making the dummy D redundant. The same definition, $z \equiv \ln(Z + D)$, is also adopted when implementing conditional nonparametric frontier estimation.

Table 1

[7] Appendix gives a more detailed description of the panel.

5 Results

5.1 SFA

Model selection

The four parametric models proposed above are estimated and then the Vuong (1989) test is performed to select the most likely one.[8] Results are reported in Table 2. The Vuong test indicates that the multiplicative specification of efficiency is preferred to the additive one, for both the input and efficiency models. It also shows that the input model is preferred to the efficiency model when comparing them in the multiplicative case. Consequently, we select the *multiplicative input model* as the most likely one at the end of the model selection procedure.

Table 2

We then proceed to test the null hypothesis that pollution abatement capital affects only the shape of the production technology as in the Coelli *et al.* (1999) model, i.e. we test the null hypothesis that $\gamma_z = \delta_{\tau z} = \delta_{kz} = \delta_{lz} = 0$ in Eq. (2).The likelihood ratio test statistics whose value is 18.616 with a p-value equal to 0.001, allow us to reject such a hypothesis.

Estimation of the preferred model

The estimated values of the parameters of the preferred model, i.e. the multiplicative input model, serve to compute the output elasticities with respect to K, L and Z and are noted as $\varepsilon_{Y,K}, \varepsilon_{Y,L}$ and $\varepsilon_{Y,Z}$. While the average values of $\varepsilon_{Y,K}, \varepsilon_{Y,L}$ and $\varepsilon_{Y,Z}$ are equal to 0.255, 0.780 and 0.018, respectively, we mainly focus our attention on the estimation of the underlying density functions. They are of interest in order to have information about the variability across firms and over time of such elasticities. In particular, we estimate the conditional densities of the above elasticities conditioned on time. Time being an ordered variable, we adopt the approach by Hall et al. (2004) which uses generalized product kernels to deal with mixed data and cross-validation to choose the smoothing parameters. We use a second order Gaussian kernel for the continuous variable and a Li and Racine's (2007) kernel for the ordered conditioning variable time. According to Hall et al. (2004), cross-validated smoothing parameters will behave in such a way that the smoothing parameters for the irrelevant conditioning variables converge in probability to the upper extremities of their respective ranges, i.e. 1 for the ordered Li and Racine's (2007) kernel. Irrelevant conditioning variables are thus smoothed out. At the other extreme, when such a smoothing parameter is zero, the generalized estimator collapses to the standard frequency estimator.

Figure 1

Figure 1 reveals that the distributions of $\varepsilon_{Y,K}$ and $\varepsilon_{Y,L}$ are clearly unimodal. Conversely, and very interestingly, it can be observed that the density of $\varepsilon_{Y,Z}$ is bimodal and appears

[8]Sectoral fixed effects have been included in the translog specification. Detailed results are available upon request to the authors.

to be a mixture of two underlying densities, a first one with a negative mode and a second one with a positive mode. Overall, about 80% of the firms have a positive elasticity. This result has two interpretations. First, it suggests that the traditional view about the effect of environmental regulation on productivity and the Porter hypothesis may coexist. Second, it reinforces the view that the firms' efforts to reduce pollution do not always positively affect the firms' performances, but they do in many cases, as also stressed by Ambec et al. (2013). Concerning the time evolution of the distributions of such elasticities, Figure 1 also reveals that the distribution of $\varepsilon_{Y,Z}$ has clearly evolved over time - the smoothing parameter for time is 0.44 - and shows a positive shift. Indeed, while at the beginning of the period, a relevant fraction of the firms are characterized by a negative elasticity, at the end of it, almost all the firms have a positive elasticity. Also note that this result could be considered as consistent with the theoretical paper by Mohr (2002) since it is observed that the annual share of firms investing in pollution abatement increased over the period (see Appendix). According to this model, firms benefit from knowledge spillovers where the amount of knowledge equals the cumulative experience of all firms using the same technology so that a specific firm will switch to a new (greener) technology only if enough other firms have done so first.

Next, we focus on the elasticities of substitution. While for a concave production function with two inputs, the elasticity of substitution among them is always positive (inputs are substitutes), in three- (or more) input production functions, as a result of the all possible interactions among inputs, an increase in one input may be associated with an increase in the use of another input, to maintain the same level of output. In such a case, these two inputs are called complements (see e.g. Chambers, 1988). To measure the degree of substitutability between any two inputs, a widely adopted measure is the Allen partial elasticity of substitution, which is defined by:

$$\sigma_{ij} = \frac{\sum_{t=1}^{T} {}_i X_i f_i}{X_i X_j} \frac{F_{ij}}{F},$$

where X_i denotes input i, $f_i \equiv \partial f / \partial X_i$, F is the determinant of the bordered Hessian of the production function whose elements are 0, f_i and $f_{ij} \equiv \partial^2 f / \partial X_i \partial X_i$. F_{ij} is the associated cofactor of f_{ij}. If $f(X)$ is concave, a factor of production cannot be a complement for all other factors in terms of the Allen elasticity. This is appealing since it appears to be intuitively consistent with the two-input case where factors are always substitutes. Figure 2 shows the estimated conditional densities of the Allen elasticities of substitution conditional on time. labor and capital, and labor and pollution abatement capital are always substitutes, with median values of the elasticities equal to 1.65 and 1.62 respectively. Their densities are tightened around a single mode and right skewed. The estimated density of Allen elasticity of substitution between capital and pollution abatement capital is also unimodal but is negatively skewed, suggesting that capital and pollution abatement capital are substitutes for most firms (the median value of the elasticity is equal to 0.16) but at the same time they are complements for other firms. Concerning the time patterns of the distributions of these elasticities, the smoothing parameter for time ranges between 0.67 and 0.72, suggesting that appreciable changes over time occurred in the overall distribution of the three partial Allen elasticities. At the same time, however, while the median value of the elasticities of substitution labor-capital and labor-pollution abatement capital does not vary significantly over time, the substitutability between capital and pollution abatement increases constantly over the period, its median varying from -0.10 in 1993 to 0.32 in 2007.

Figure 2

Finally, note that natural outcomes of the estimation of the multiplicative input model are the time-varying efficiency scores. They can be computed as $\exp\left(-\mathbb{E}\left(u_{it}|\varepsilon_{i1},\ldots,\varepsilon_{iT_i}\right)\right)$ where $\varepsilon_{it} = v_{it} - u_{it}$, using an extension of the Jondrow *et al.* (1982) estimator of efficiency score to the input model with multiplicative efficiency. At the same time, however, they are not a central interest of this paper and detailed results on these scores are available upon request.

5.2 CNFA

To complement the previous analysis, we conduct the CNFA analysis detailed above. CNFA may serve to detect a possibly complex nonlinear effect of pollution abatement capital on the production process. Moreover, CNFA also permits us to understand whether external factors affect both the shape of the frontier and the distribution of efficiencies.

As a first step, we investigate the ratios of conditional and unconditional efficiency measures for full and partial frontiers. The conditional DEA estimates are computed with the localizing procedure described in Mastromarco and Simar (2015) and optimal bandwidths have been selected by least squares cross-validation. Figure 3 shows the ratios from a marginal point of view, i.e. as a marginal function of pollution abatement capital.[9] The full frontier ratios (top panel) show a nonlinear effect of pollution abatement capital on the shape of the frontier. This nonlinear effect takes the shape of an inverted U relation suggesting the existence of a positive effect on the shape of the frontier when pollution abatement capital increases at low values of capital and a decreasing effect for large values of capital. In order to check the robustness of our result and to inspect whether some extreme observations would hide an effect, we calculated the ratios for partial frontiers with $\alpha = 0.99$, and obtained very similar results, which are available upon request. According to Bădin et al. (2012), the full frontier ratios also provide useful information on the ‘separability condition’, which in this case, seems clearly to be violated, because our external variable - pollution abatement capital - is affecting the boundary of the production set (shifts of the production frontier).

Turning to “low order” partial frontier ratios, looking at the center of the distribution ($\alpha = 0.5$) (effect on the median of the distribution of Y given that $X \leq x$), Figure 3 (bottom panel) displays a slightly favorable effect of pollution abatement capital. We observe a very flat relation for most of the range of pollution abatement capital which becomes positive for the highest values of such a variable.[10]

[9]The plots of the ratios expressed as a marginal function of time are available upon request.

[10]The results are very stable to changes in the quantile. Detailed results obtained for other values of α are available upon request.

These results seem to confirm our previous parametric ones that pollution abatement capital acts more as production factor, affecting the shape of the frontier, than a productivity factor, influencing the inefficiency. Thus pollution abatement capital impacts mainly on the shift of the boundary and less on the distribution of inefficiencies. Hence, from this evidence, pollution abatement capital appears to weakly affect efficiency (technological catch-up) and play a more important role in accelerating technological change (shifts in the frontier).

Figure 3

Given that the separability assumption is not verified, in order to analyze and isolate the effect of pollution abatement capital and time on the distribution of efficiencies, it is necessary to move to the second-step nonparametric regression using conditional efficiency scores as a dependent variable.[11] Consequently, in the second step, as suggested by Bădin et al. (2012) and Mastromarco and Simar (2015), we regress the log of conditional efficiency scores as a function of pollution abatement capital (in logs) and time.[12] We use Generalized Local Polynomial Kernel Regression by Hall and Racine (2015) to estimate the location effect. Bernstein polynomials are employed (note that a Bernstein polynomial is also known as a Bezier curve) and the generalized product kernel is obtained as a product of a second order Gaussian kernel for the continuous predictor, pollution abatement capital, and a Li and Racine's (2007) kernel for the ordered variable time. The delete-one cross validation procedure provides a first order local polynomial for pollution abatement capital and bandwidths equal to 0.223 and 0.172, for pollution abatement capital and time, respectively. According to Hall et al. (2007), these results indicate that both regressors are relevant.

Figure 4

Figure 4 shows that pollution abatement capital has a nonlinear effect on the conditional efficiencies. Indeed, for very low levels of pollution abatement capital, the conditional efficiency scores $\log\tau(x, y|z)$ - pollution abatement capital relation is quite flat, suggesting that a minimum level of capital devoted to pollution abatement is necessary to produce an effect. Then, after reaching a threshold, this relation is no longer flat but roughly shows an inverted U pattern. We clearly see negative and then positive average effects of pollution abatement capital on conditional efficiency (a decrease of $\log\tau(x, y|z)$ indicates an increase in efficiencies, the optimum being zero).

The effect of pollution abatement capital seems much more important than the effect of time, except for small values of pollution abatement capital. This finding suggests that pollution abatement capital needs to reach a certain level to drive efficiency externalities. The effect of time is less important for large values of pollution abatement capital, supporting the hypothesis of decreasing adjustment costs and time delays.

[11] Indeed, if the separability condition is not verified, unconditional efficiency scores do not provide useful information since they ignore the heterogeneity introduced by the external variables on the attainable sets of values for (X, Y).

[12] The log transform is natural when analyzing ratios as conditional efficiency scores.

The bottom two panels of Figure 4 exhibit the marginal view from the perspective of time and abatement pollution capital.[13] This evidence, combined with the previous ones, highlights the nonlinear influence of pollution abatement capital on efficiency. The time shows a slight positive effect on efficiency revealing a very slow technological catching-up process among the firms under analysis.

In summary, these results complement the previous ones obtained using parametric frontiers. Indeed, on the one hand, comparing these nonparametric findings with the elasticity obtained from the preferred parametric input model, provides confirmation of the existence of a heterogeneous effect of pollution abatement capital on the shape of the frontier but also suggests a particular shape (inverted U) without imposing a specific functional form. On the other hand, when we estimated the parametric efficiency model in equation (7) we found that pollution abatement capital has a positive - but low in magnitude and not significant - effect on efficiency. This possibly was the result of the imposed parametric specification and distribution assumptions on the error terms, since the second-step nonparametric regression performed in this section indicates a rather complex nonlinear relation. To our knowledge, this is the first econometric work showing the existence of a non-monotonic effect as suggested, for instance, by André (2015).

6 Conclusions

This paper estimates the impact of pollution abatement investments on the production technology of firms, using a novel and rich panel data set covering the French food processing industries over the period 1993-2007. It aims to contribute to the literature by pursuing two new directions. First, with respect to a methodological perspective, we take advantage of recent developments in productivity and efficiency analysis that allow the consideration of external factors of production. Specifically, we compare the results obtained with two complementary approaches: parametric stochastic frontier analysis and conditional nonparametric frontier analysis. These methods present relative advantages and drawbacks and comparing their results may be useful to provide a more nuanced and thorough picture of the effect of pollution abatement investments on the production technology of firms. A second novel aspect of this paper is its empirical and policy-oriented perspective, since we pay attention not only to the average effect but also on its variability across firms and over time, and search for eventual nonlinearities. These aspects have been recognized as extremely relevant by the theoretical literature and have important implications for firms and society as a whole in terms of advice on environmentally friendly policy.

We provide new results suggesting that the effect of pollution abatement capital on the shape of the production frontier is heterogeneous both within firms and over time, and reinforcing the view that firms' efforts to reduce pollution do not always positively affect their performances, but do in some cases. We have also documented that the substitutability between pollution

[13] These pictures shows the surface of the top panel of Figure 4 from the perspective of pollution abatement capital and time, respectively by fixing the value of other regressor to its mean.

abatement capital and physical capital increases constantly over the period. Finally, when switching to a fully nonparametric framework, relevant complementary results are provided. In particular, using this approach it was possible to uncover a nonlinear and non monotonic effect of pollution abatement capital, both on the shape of the frontier and on the conditional efficiencies. These results have relevant implications both for modeling purposes and in terms of policy advice.

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Appendix: Description of the panel

Let us first focus on firms' pollution abatement investments. The share of firms investing in pollution abatement activities at least one year during the period 1993-2007, for the 1130 firms constituting the unbalanced panel, is equal to 85.22%. Figure 5 reports the percentages of non investing firms in the different sectors of the French food processing industry.[14] Pollution abatement investment behaviours are different across sectors. All firms invested at least once in the highly polluting starch and vegetable fats and oils manufacturing sector, while only two thirds of firms did so in the beverage sector.

Figure 5

Consider now the trends in pollution abatement investments. The annual share of investors increases from 51.95% in 1993 to 65.16% in 2007, as shown in Figure 6. Such an increase is mostly due to a level shift that occurred from 2000 to 2001 when the share of firms investing to reduce pollution moved from 53.06% to 68.82%. This is likely due to stricter environmental constraints. In 2000, indeed, the European Union promulgated a relevant directive, i.e., the EU water framework directive, aiming to achieve a good status for all waters and introducing new standards for managing Europe's waters (see e.g., Kallis and Butler, 2001). The treatment of waste water is one of the most important fields for pollution abatements, concerning on average more than 50% of the total pollution abatement investments of the French food industry. At the same time, when focusing only on the firms investing in pollution abatements, it can be noted that the average amount of investments decreases from 320.932 KEuros in 1993 to 247.261 KEuros in 2007 and that this decrease occurred in the 2000s, as shown in Figure 6.

Figure 6

[14] The French food industry can be broken down into 10 sectors when the NACE classification at the 3-digit aggregated level is considered.

Table 1: Summary statistics

Variable	Label	Mean	Std. dev.
Value-Added (K Euros)	Y	27605.71	52847.71
labor (Number of workers)	L	418.03	534.38
Capital stock (K Euros)	K	47756.40	104830.80
Pollution Abatement Capital stock (K Euros)	Z	980.53	2575.60

Table 2: Model selection results

Null Hypothesis	Vuong Test Statistics (V)	P-value
Additive vs Multiplicative (Input model)	-24.458	< 0.001
Additive vs Multiplicative (Efficiency model)	-24.531	< 0.001
Input model vs Efficiency model (Multiplicative case)	5.3142	< 0.001

Notes.
The Vuong statistic, V, is asymptotically distributed as standard normal distribution.
If $V > 1.96$, then the first model is favored at 5% significance level.
If $V < -1.96$, then the second model is favored at 5% significance level.
Otherwise, for $-1.96 \leq V \leq 1.96$, neither model is preferred.

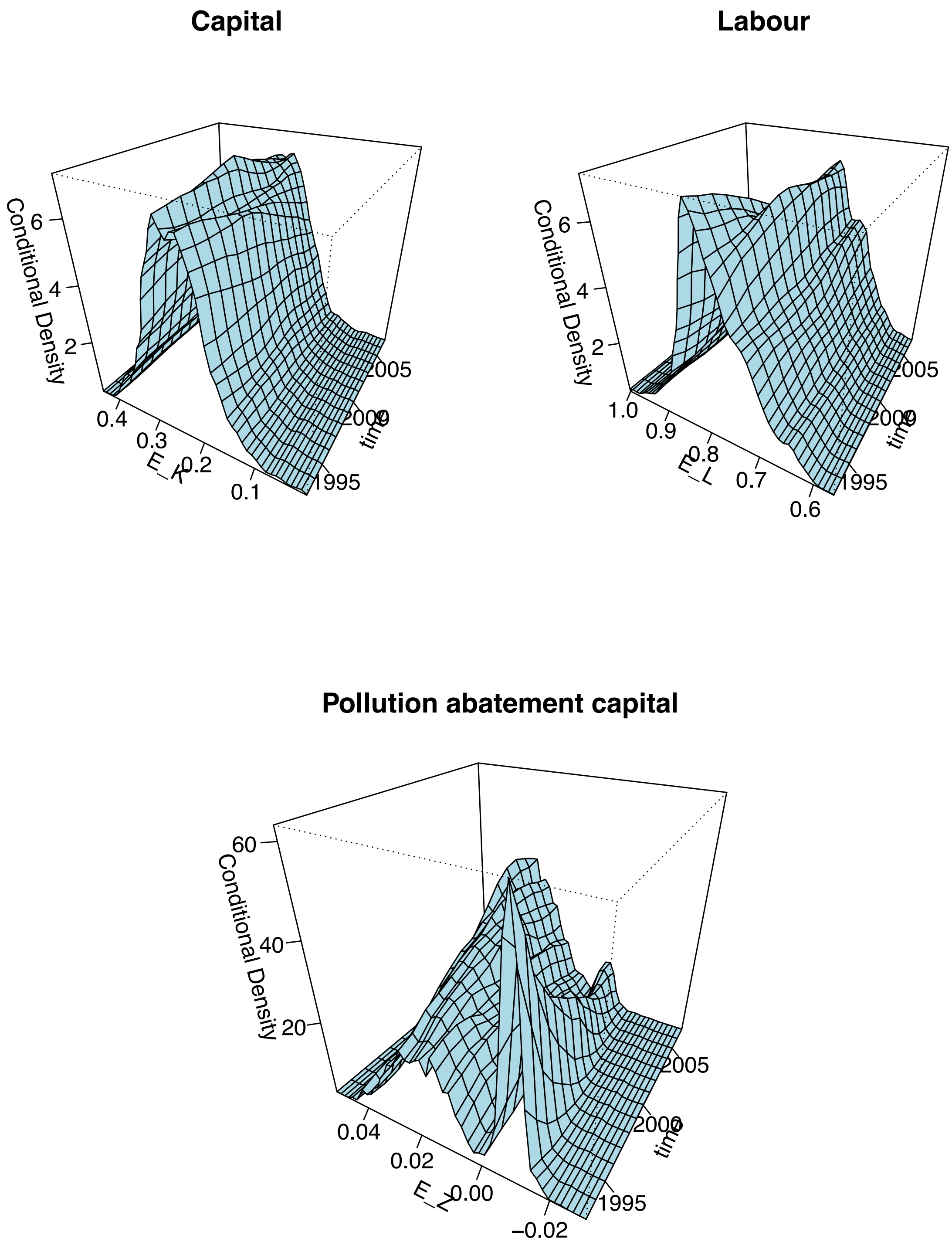

Figure 1: Estimated conditional densities of elasticties

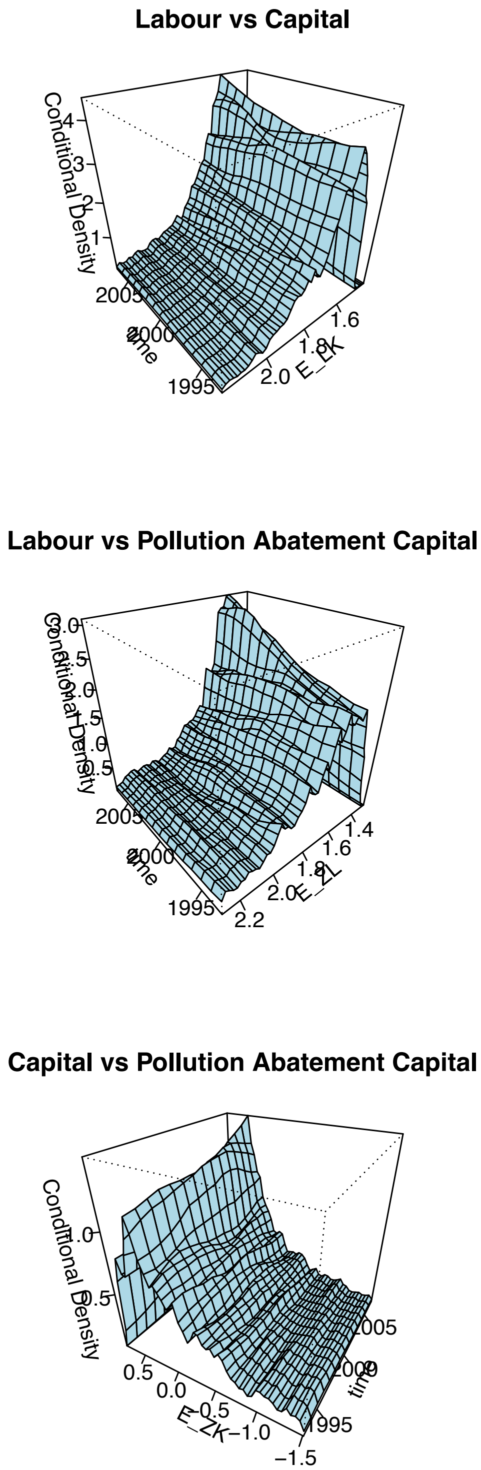

Figure 2: Estimated conditional densities of Allen partial elasticities of substitution

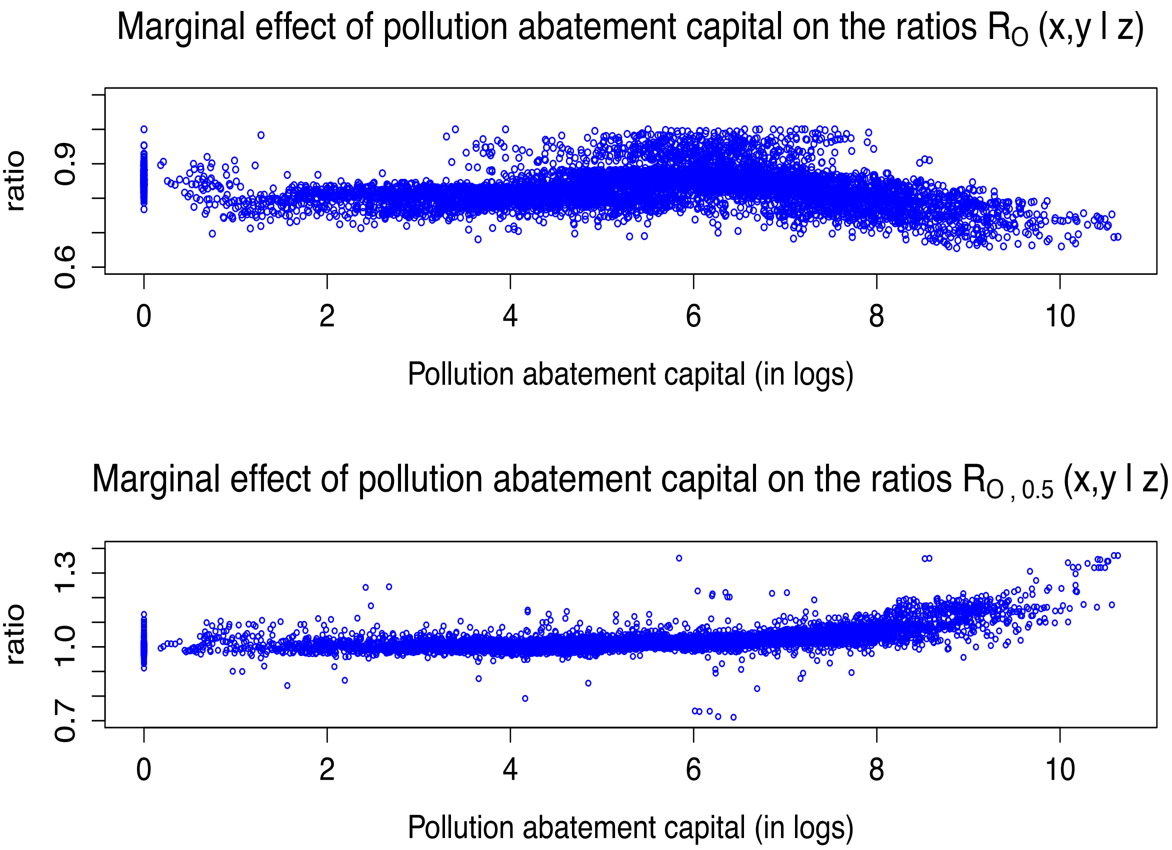

Figure 3: *The top panel represents the full ratio* $\widehat{R}_O(x, y|z)$ *as a marginal function of pollution abatement capital (in logs). The bottom panel is the ratio* $\widehat{R}_{O,\alpha}(x, y|z, t)$ *for* $\alpha = 0.5$*, so for the median-order efficiencies.*

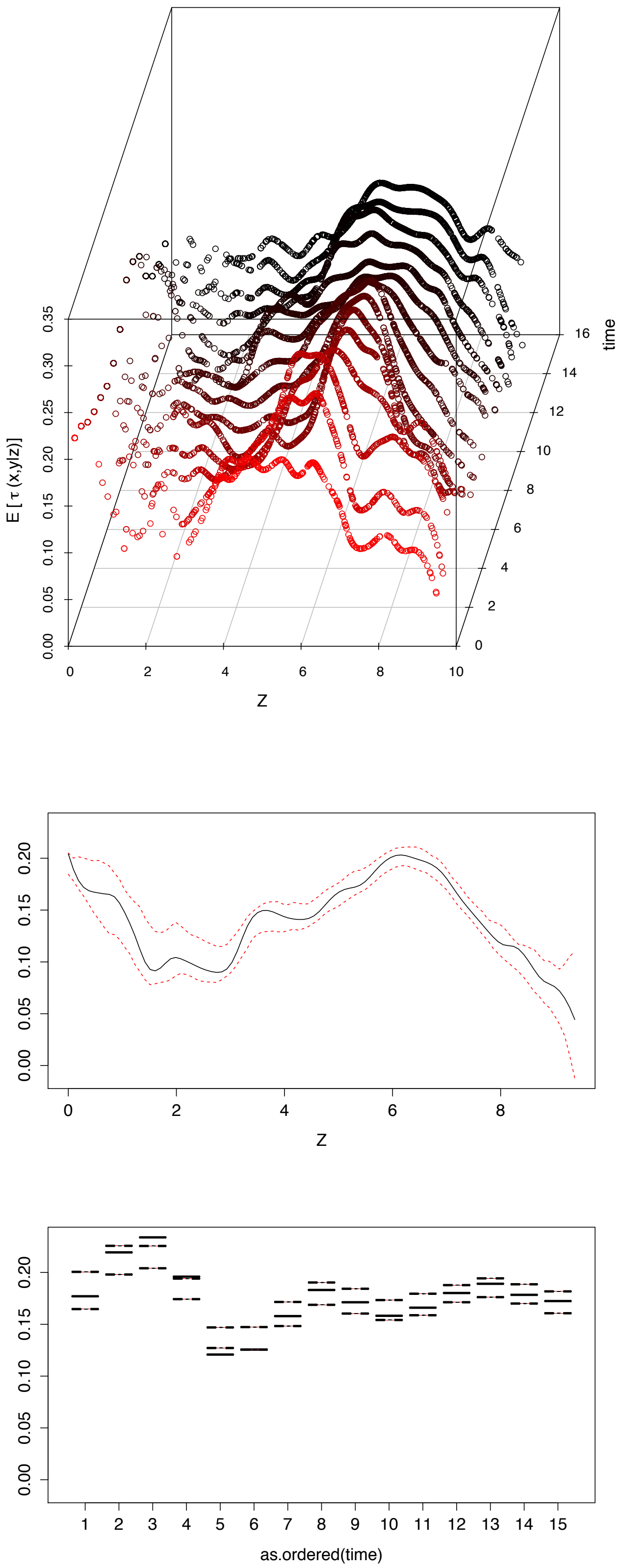

Figure 4: Estimated location effect of conditional efficiency scores (top panel), and their two marginal views (bottom panel), as function of pollution abatement capital (in logs) and time. Generalized Local Polynomial Regression is employed. Here we use the $\log(\tau(x, y|z))$ as the dependent variable. The two marginal views are obtained by fixing the value of the other regressor to its mean. 95% bootstrapped confidence bands are also reported.

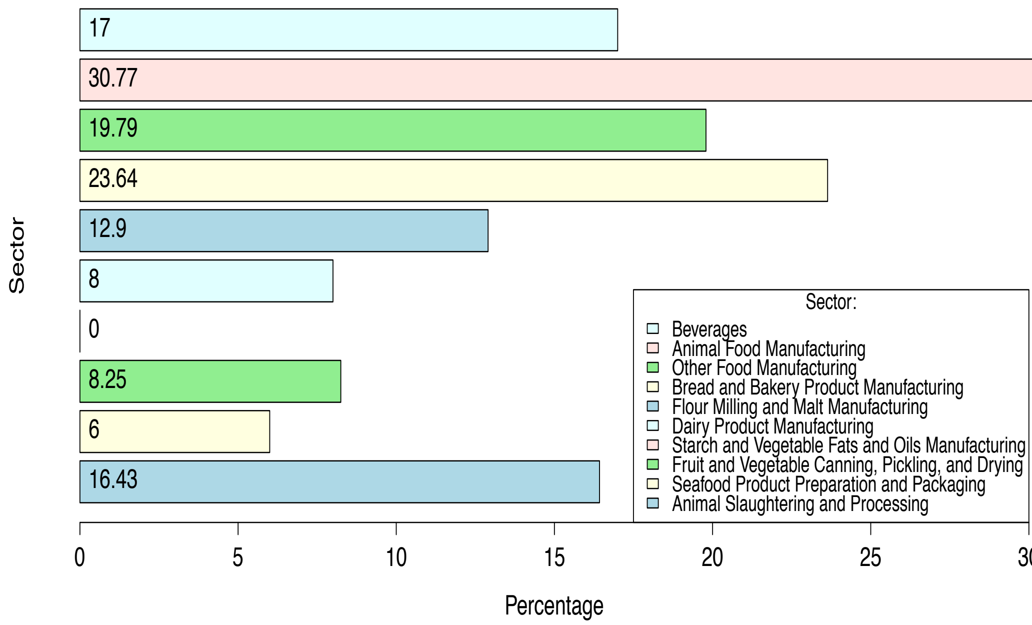

Figure 5: Percentages of pollution abatement non investing firms in food processing industry sectors

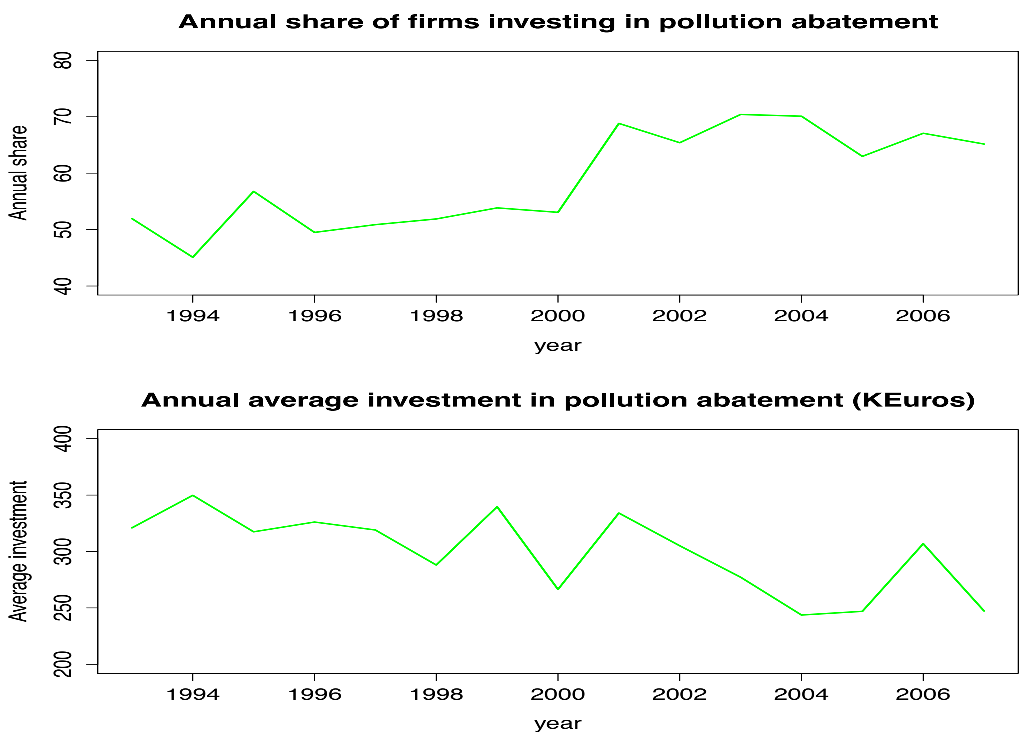

Figure 6: Trends in pollution abatement investments