The impact of pollution abatement investments on production technology: a nonparametric approach

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Abstract

This paper estimates 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, efficiency analysis and nonparametric kernel regression by adopting a conditional nonparametric frontier analysis. Second, we focus not only on the average effect but also search for potential nonlinearities. We provide new results suggesting that pollution abatement capital affects with a bell-shaped fashion technological catch-up (inefficiency distribution) and does not affect technological change (shifts in the frontier). These results have relevant implications both for modeling and for the purposes of advice on environmentally friendly policy.

Keywords: Pollution abatement investments, technology, conditional nonparametric frontier analysis, full and partial order frontiers, location-scale nonparametric regression, infinite order cross-validated local polynomial regression, separability condition.

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 mixed empirical evidence, so that the validity of the Porter hypothesis continues to be one of the most contentious issues in the debate regarding environmental regulation. All this suggests 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 a method that has 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 modeling 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, a conditional nonparametric frontier analysis (CNFA) is adopted in this paper. Compared to parametric stochastic frontier analysis, CNFA has the relative advantage 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. 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.) but it may be extremely useful when the goal is detecting possibly complex nonlinear relations, as in the case of the present work.

More specifically, we build on previous works adopting a two-step approach (e.g. 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, a location-scale nonparametric regression model is adopted to go further into the analysis of the impact of external factors. We follow recent advances in econometric theory and depart from previous works in two ways. First, after the first step, we propose an intermediate step where we focus attention on the 'separability' condition from Simar and Wilson (2007, 2011) according to which the external factors do not influence the boundary of the attainable set, and the effect on the production process is eventually only through the distribution of the inefficiencies. We specifically adopt the recently proposed test by Daraio et al. (2017). This is crucial in order to choose the appropriate dependent variable – unconditional or conditional efficiency scores – for the last-step regression model. Second, as far as the last-step nonparametric kernel regression is concerned, we avoid ad hoc determination of the local polynomial order by using the 'infinite order cross-validated local polynomial regression approach' recently proposed by Hall and Racine (2015). This method allows – via delete-one cross-validation – the joint determination of the polynomial order and bandwidth and this 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 a method 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 methodology 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. 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

3.1 Overview and modeling purposes

There is a huge body of econometric literature testing the strong version of the Porter hypothesis, but it provides a rather mixed empirical evidence (Ambec et al., 2013), so that the validity of such an hypothesis is still a very contentious issue.

The common practice consists at adopting parametric production functions or productivity equations augmented with some measures of pollution abatement efforts. In this paper, we follow a different path, and precisely we adopt the same view than Broberg et al. (2013) who consider pollution abatement investments as an external factor of production. External factors 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.

Broberg et al. (2013, p. 47) precisely assume that *"these investments are being exogenously enforced on firms via environmental regulation"*. More generally, the existence of a strong link between environmental regulation and pollution abatement investments decisions has been largely recognized in the literature, see e.g. Gray and Shadbegian (1998, 2003), who *"find that new plants in more stringent states are less likely to incorporate the dirtier production technologies"* (Gray and Shadbegian, 1998, p. 254). Similarly, Acemoglu et al. (2016) and Aghion et al. (2016) show both theoretically and empirically that environmental policies have a crucial role to stimulate green investments. In summary, the literature provides a clear evidence according to which pollution abatement investments are largely pushed by environmental policy. This makes the adoption of a statistical framework where pollution abatement capital enters as an external factor reasonable, also in view of the complementary useful insights that it can provide with respect to the standard approach, especially when adopting a nonparametric framework.

To deal with external factors, a first and quite common approach consists at adopting a parametric stochastic frontier analysis and modeling the impact of external factors either on the structure of the technology or on technical efficiency (Coelli et al, 1999; Kumbhakar and Lovell, 2000). Following this literature, Broberg et al. (2013), adopt the Battese and Coelli (1995) approach and introduce pollution abatement investments as a determinant of technical inefficiency.

The parametric approach allows the estimation of some key parameters 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. To relax these restrictive parametric assumptions, we use a CNFA. Allowing for possible nonlinear effects is particularly relevant from a policy-oriented perspective and is consistent with the theoretical literature. Moreover, using recent developments in nonparametric frontier literature (Daraio and Simar, 2005 and 2007; Bădin et al., 2012, 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. Moreover, by using a time-dependent approach similar to Mastromarco and Simar (2015) we can take into account time delays and adjustment costs in the production process.

Despite this paper represents, to the best of our knowledge, the first attempt to use CNFA to test the strong version of Porter hypothesis, it is worth mentioning the existence of a literature that have applied conditional efficiency analysis in a field of application close to the one addressed in paper (Halkos and Tzeremes; 2012, 2013, 2014; Halkos and Managi, 2016; Halkos et al., 2016).This literature aims to explain environmental efficiency as a function of some external factors, such as environmental policy among others.

Below, we briefly recall how external variables can be introduced in the nonparametric analysis of production boundaries. We then describe the three-step approach employed to characterize the nature of the impact of external variables on the production process and the efficiency of firms.

3.2 Conditional nonparametric frontier analysis

Nonparametric frontier analysis is based on a statistical model of the production process along the lines of the probability framework initiated by Cazals et al. (2002). 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 environmental factors, i.e. factors that may influence the production process and the efficiency pattern (in our framework, pollution abatement capital). As shown by Daraio and Simar (2005, 2007) and Mastromarco and Simar (2015), the production process can be described by

$$H_{X,Y|Z}^{t}\left(x, y|z\right) = Prob\left(X \leq x, Y \geq y|Z = z, T = t\right). \tag{1}$$

The function $H_{X,Y|Z}^{t}\left(x, y|z\right)$ is simply the probability for a firm operating at level (x, y) to be dominated by firms facing the same environmental conditions z and operating at time t. Given $Z = z$ and $T = t$, the range of possible combinations of inputs and outputs, we denote by Ψ_t^z, is fully defined by the support of $H_{X,Y|Z}^{t}\left(x, y|z\right)$. Accordingly, the conditional output-oriented technical efficiency of a production plan $(x, y) \in \Psi_t^z$, i.e. facing environmental conditions z at time t, can be defined as

$$\tau_t\,(x, y|z) = \sup\{\tau|(x, \tau y) \in \Psi_t^z\} = \sup\{\tau|S^t_{Y|X,Z}(\tau y|x, z) > 0\}.$$

where $S^t_{Y|X,Z}(y|x, z = \text{Prob}(Y \geq y|X \leq x, Z = z, T = t)$ is the (nonstandard) conditional survival function of Y, nonstandard because the condition on $X \leq x$ and not $X = x$.

Let $H_{X,Y}(x, y)$ denote the unconditional probability of being dominated, i.e.

$$H_{X,Y}\,(x, y) = \text{Prob}(X \leq x, Y \geq y) \tag{2}$$

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

$$\tau(x, y) = \sup\{\tau|(x, \tau y) \in \Psi\} = \sup\{\tau|S_{Y|X}(\tau y|x) > 0\}, \tag{3}$$

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

To obtain robust results to some extreme observations, partial frontiers can be also estimated. Robust order-α quantile efficiency measures were introduced by Daouia and Simar (2007). Conditional (unconditional) output-oriented robust order-α quantile efficiency measures are defined for any $\alpha \in (0, 1)$ as:

$$\begin{aligned} \tau_{t,\alpha}(x, y|z) &= \sup\{\tau|S_{Y|X,Z}(\tau y|x, z, t) > 1 - \alpha\} \\ \tau_{\alpha}(x, y) &= \sup\{\tau|S_{Y|X}(\tau y|x) > 1 - \alpha\} \end{aligned} \tag{4}$$

3.3 Assessing the impact of external variables and time

3.3.1 Exploratory analysis

As stated in Bădin et al. (2012) and in Mastromarco and Simar (2015), the effect of external factors on the boundary can be investigated by considering the ratios of conditional to unconditional efficiency measures, which are measures relative to the full frontier of the conditional and the unconditional attainable production sets, respectively, i.e.

$$R_{t,O}(x, y|z) = \frac{\tau_t(x, y|z)}{\tau(x, y)}. \tag{5}$$

By construction, $R_{t,O}(x, y|z) \leq 1$, whatever the quadruplet (x, y, z, t). 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 different values of α, i.e

$$R_{t,O,\alpha}(x, y|z) = \frac{\tau_{t,\alpha}(x, y|z)}{\tau_{\alpha}(x, y)}. \quad (6)$$

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

For the output orientation, when the ratios (5) 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 $\tau_t(x, y|z,)$ 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 (5) 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 $\tau_t(x, y|z)$ 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 (5) indicate only the effects of external factors on the shape of the frontier, whereas with the partial frontier ratios (6), 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.[1]

Nevertheless, the conclusions of the exploratory 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.

3.3.2 Separability condition

To go further into the analysis of the impact of external factors, a nonparametric regression modelcan be adopted to analyze the average behaviour of $\tau(x, y)$ as a function of z and t. However, this approach requires a restrictive separability condition between the input/output space and the space of external factors, assuming that these factors have no influence on the attainable set, affecting only the probability of being more or less efficient. If this separability

[1]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.

condition is rejected, as suggested by Bădin et al. (2012), in the second stage it is meaningful to analyze the average behaviour of the conditional efficiency scores $\tau_t(x,y|z)$ - rather than the unconditional ones $\tau(x,y)$ - as a function of the external factors. The conditional efficiency scores $\tau_t(x,y|z)$ may also vary with both z, t and x, but if one wants to capture the marginal effect of external factors on the efficiency scores, it is legitimate to analyze the regression model $\mathbb{E}\left(\tau_t(x,y|z)|Z=z,T=t\right)$ as a function of z and t.

Hence, to assess the impact of our Z variable (the pollution abatement capital stock) on the production process - shape of the frontier and efficiency distribution - and to choose the appropriate dependent variable for the second-stage regression model, we consider the "separability" assumption from Simar and Wilson (2007, 2011). As explained in Simar and Wilson (2007, 2011) the "separability" assumption assumes that the frontier of the attainable set does not depend on the values of Z. Formally, denote by Ψ the marginal attainable set and Ψ_t^z the support of of the conditional probability $H^t_{X,Y|Z}(x,y|z)$, i.e. the set of attainable points in the input-output space of firms facing the external conditions $Z=z$ at time $T=t$. Under the "separability" condition we have $\Psi_t^z \equiv \Psi$ for all (z,t), i.e. Z does not influence the shape (the boundary) and/or the level of the attainable set.

As explained in Simar and Wilson (2007, 2011), when the separability condition is not verified, the marginal measures of efficiencies, computed relatively to boundary of the marginal attainable set Ψ, i.e. $\tau(x,y)$, have no particular economic meaning because each observed production plan will be benchmarked against an unattainable frontier facing conditions z at any particular time t.

Daraio et al. (2017), by developing central limit theory (CLT) and using the CLT results for both unconditional and conditional efficiencies, suggest a test of the null hypothesis of separability versus the alternative of non-separability. For that purpose, they compare the distributions of conditional and unconditional efficiency scores using relevant statistics on $\tau(x,y)$ and $\tau_t(x,y|z)$.

Following Daraio et al. (2017), to implement the test we first randomly split our data sample in two independent parts n_1 and n_2 and use them to compute conditional and unconditional estimates.[2] Second, we compute the estimates of the averages in the two independent samples:

$$\widehat{\mu}_{n_1} = \frac{1}{n_1}\sum_{i=1}^{n_1} \widehat{\tau}(X_i,Y_i), \text{ and } \widehat{\mu}_{n_2} = \frac{1}{n_2}\sum_{i=1}^{n_2} \widehat{\tau}(X_i,Y_i|Z_i)$$

and the corresponding variances:

$$\widehat{\sigma}^2_{n_1} = \frac{1}{n_1}\sum_{i=1}^{n_1} \left(\widehat{\tau}(X_i,Y_i) - \widehat{\mu}_{n_1}\right)^2, \text{ and } \widehat{\sigma}^2_{n_2} = \frac{1}{n_2}\sum_{i=1}^{n_2} \left(\widehat{\tau}(X_i,Y_i|Z_i) - \widehat{\mu}_{n_2}\right)^2$$

Third, we estimate also the bias for a split of each subsample for the unconditional $\widehat{\beta}_{n_1}$ and

[2]Note that, due to the panel structure of our sample, we compute the test for the first and last year to assure time independence.

conditional cases $\widehat{\beta}_{n_2}$. Finally, we compute the test statistics

$$\frac{(\widehat{\mu}_{n_1} - \widehat{\mu}_{n_2}) - \left(\widehat{\beta}_{n_1} - \widehat{\beta}_{n_2}\right)}{\sqrt{\frac{\widehat{\sigma}^2_{n_1}}{n_1} + \frac{\widehat{\sigma}^2_{n_2}}{n_2}}}$$

Under the null of non separability, because the bias-corrected sample means are independent and two sequences of independent normal limiting distributed variables have a joint bivariate normal distribution, this test statistics can be shown to be asymptotically distributed as a standard normal distribution.

3.3.3 Efficiency scores as a function of external variables and time

If the separability condition is not rejected, a regression model employing unconditional efficiency scores as dependent variable can be adopted. Otherwise, conditional scores should be used. Since the results of the separability test by Daraio et al. (2017), which are detailed afterwards, indicate that the separability condition cannot be rejected, we employ unconditional efficiency score, $\tau(x, y)$, and specifically focus on the following nonparametric location-scale regression function (see, e.g. Fan and Gijbels, 1996):

$$\tau(x, y) = \mu(z, t) + \sigma(z, t)\varepsilon \tag{7}$$

where $\mu(.)$ and $\sigma(.)$ are unknown smooth functions to be estimated and ε is the usual error term such that $\mathbb{E}(\varepsilon|Z = z, T = t) = 0$, and $\mathbb{V}(\varepsilon|Z = z, T = t) = 1$.

In such a specification, the location effect, $\mu(z, t)$, is of primary interest here, while the variance function, $\sigma^2(z, t)$, also known as the scale effect, may provide some useful complementary insights. They can be expressed, respectively, as

$$\mu(z, t) = \mathbb{E}\left(\tau(x, y)|Z = z, T = t\right), \text{ and } \sigma^2(z, t) = \mathbb{V}\left(\tau(x, y)|Z = z, T = t\right). \tag{8}$$

To estimate this model, we follow recent advances in nonparametric kernel regression and depart from the above-mentioned works which estimate location-scale regression models with the local constant approach, or more generally choosing ad hoc the order of the local polynomial. We instead use the 'infinite order cross-validated local polynomial regression approach' recently proposed by Hall and Racine (2015) which allows – via leave-one-out 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 data generating process (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, $O(n^{-1/2})$.[3]

[3]The computations are performed thanks to the `npglpreg` function from the `crs` library in the R language

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 is particularly relevant for such a kind of analysis 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) - and it is one of the sectors investing more in pollution abatement.[4] It is finally also 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).

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.[5] This table shows that average pollution abatement capital stock is about two percent 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). All the continuous variables used in the CNFA are expressed in logarithms. To include all the observations for the pollution abatement capital stock, pac, we set $z \equiv \ln(pac + d)$ where $d = 1$ if $pac = 0$, and $d = 0$ if $pac > 0$, as external variable, instead of setting $z \equiv \ln(pac)$ which is

(see Nie and Racine, 2012, for a general presentation).

[4]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.

[5]A detailed description of the panel is given in Appendix 1.

not defined when $d = 1$.

Table 1

5 Results

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.

Conditional and unconditional efficiency measures, which are employed for the analysis, are computed by using the free-disposal hull (FDH) method with the localizing procedure described in Mastromarco and Simar (2015) and optimal bandwidths have been selected by least squares cross-validation. The FDH estimator is used because it relaxes the assumption of convexity of the production set, which is imposed in data envelopment analysis (DEA) and which is often a too restrictive assumption (Daraio and Simar, 2007).

5.1 Explanatory tools

In a first step, we investigate the ratios of conditional and unconditional efficiency measures for full and partial frontiers. Figure 1 shows the full frontier ratios from a marginal point of view, i.e. as a marginal function of pollution abatement capital and time, respectively. With such a full frontier plots, we can assess possible effects on the boundary (shift of the frontier).

The full frontier ratios do not highlight any clear effect of pollution abatement capital and time on the boundary of the attainable set. 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.

As far as "low order" partial frontier ratios are concerned, looking at the center of the distribution, or median ($\alpha = 0.5$), Figure 2 (top panel) displays a slightly favorable effect of pollution abatement capital. We observe a slightly positive relation for most of the range of pollution abatement capital, which becomes more sloped for the highest values of such a variable. The bottom panel represents the same ratios as a marginal function of time and indicates that the distribution of such ratios is quite stable over time.[6]

In summary, these results suggest that pollution abatement capital acts as a 'productivity factor', influencing the efficiency while it does not play a role of a 'production factor', affecting the frontier of the attainable set. In other words, pollution abatement capital appears to affect technological catch-up (inefficiency distribution) and does affect technological change (shifts in the frontier).

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

Finally, according to Bădin et al. (2012), the analysis of the ratios detailed above may provide some information on the "separability condition", according to which the external factors do not influence the boundary of the attainable set, and their effect on the production process is eventually only through the distribution of inefficiencies. In this case, there is not a clear descriptive evidence that such a hypothesis is violated. This issue will be further investigated using a formal test in a second step.

Figures 1 and 2

5.2 Testing the separability condition

If the separability condition is not verified, using unconditional efficiency scores as dependent variable for the second-stage regression does not provide useful information since they ignore the heterogeneity introduced by the external variables on the attainable set.

As a second step, we test the separability condition, $\Psi_t^z \equiv \Psi$, using two randomly selected subsamples and FDH estimators in output direction, with bandwidths obtained by least-squares cross-validation adjusted to obtain the optimal order as discussed in Daraio et al. (2017). Note that there are many possible splits of the data and that the results may vary over these splits. Since combining information across many splits of a given sample does not allow obtaining meaningful results, the two subsamples are selected using the algorithm proposed by Daraio et al. (2017).[7] Moreover, since the test is suitable for cross-sectional data, we compute the test for the first year, the median year and the last year. The results are clear-cut: in all cases, the null of separability cannot be rejected with p-values higher than 0.29.

The explanatory tools and the separability test provide us an important and clear result according to which there is no evidence that pollution abatement capital influence either the shape or the level of the boundary of the attainable set. The eventual effect of pollution abatement capital on the production process is only through the distribution of the inefficiencies and this possibility will be investigated in the next section.

Given that the separability condition cannot be rejected in our data sample, in a last step, we will analyze the behaviour of the unconditional efficiency scores $\tau(x, y)$ as function of z and t.

5.3 Nonparametric location-scale regression

In this last step, as suggested by Bădin et al. (2012) and Mastromarco and Simar (2015), to better explore possible nonlinear effects, we adopt a nonparametric regression model. In particular, we regress the log of unconditional efficiency scores as a function of the log of pollution abatement capital and time. We use the method proposed by Hall and Racine (2015) to estimate the location-scale effects. Bernstein polynomials are employed (note that a Bernstein polynomial is also known as a Bezier curve) and the generalized product kernel is

[7] We are grateful to Léopold Simar for providing Matlab code to compute the separability test.

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.

We first focus on the location effect, $\mu(z,t)$ in (7). The leave-one-out cross validation procedure chooses the local-constant estimator for pollution abatement capital and bandwidths which are equal to 0.472 and 0.667 for pollution abatement capital and time respectively. These bandwidths have a clear interpretation indicating that both pollution abatement capital and time are relevant in order to explain unconditional efficiency scores. This because, according to Hall et al. (2004) and Hall and Racine (2007), 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 (see also Kiefer and Racine, 2017). The same kind of argument can be used for continuous predictors, but only in the special case of the local-constant estimator: in such a case, a bandwidth going to infinity will produce a constant fit, thus suggesting that the regressor is irrelevant.

Figure 3 displays the results of the estimation of the location effect and provides us the main result of the paper: pollution abatement capital appears to have a nonlinear effect on the efficiencies. For very low levels of pollution abatement capital, the unconditional efficiency scores $\log\tau(x,y)$ - pollution abatement capital relation is quite flat. This could suggest that a minimum level of capital devoted to pollution abatement is necessary to produce an effect. However, for such low levels of pollution abatement capital, there is a scarcity of data that makes difficult to identify a clear pattern. Then, after reaching a threshold, data become more dense and the relation roughly shows an inverted U pattern. This indicates first a negative and then a positive average effect of pollution abatement capital on unconditional efficiency. Note that a decrease of $\log\tau(x,y)$ indicates an increase in efficiencies, the optimum being zero. This finding suggests that, in order to obtain a positive effect, pollution abatement capital needs to reach a certain level to drive efficiency externalities. Such a result is extremely relevant with respect to both theory and policy implications. First, it suggests that the traditional view about the effect of environmental regulation on productivity and the Porter hypothesis may coexist. Second, it not only 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), but it also provides the specific pattern of the 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).

Looking at the effect of time, a first look at the 3D plot seems to indicate that such an effect is less important in magnitude than the one of pollution abatement capital. The bottom two panels of Figure 3 exhibit the marginal view from the perspective of abatement pollution capital and time. Each marginal view reports the estimated conditional mean of unconditional efficiency scores as a function of each of the two variables, fixing the other variable at its median value. 95% bootstrapped confidence bands are also reported. These plots complement the previous one and indicate that, overall, when fixing pollution capital abatement at its median value it is observed a slightly inverted U effect of time on inefficiency.[8]

Figure 3

We then estimate the scale effect $\sigma^2(z,t)$. The leave-one-out cross validation procedure chooses a cubic-order local polynomial for pollution abatement capital and bandwidths which are equal to 1.691 and 0.880 for pollution abatement capital and time respectively. These results confirm the importance of using cross-validation to choose the polynomial order, while otherwise this choice is difficult since any arbitrary choice will face a bias-variance trade-off those exact magnitude will depend on the unknown DGP (see also Fan and Gijbels, 1996, p. 76-80). They also indicate that time is a relevant variable to explain the scale effect, even if a bandwidth equals to 0.880 suggests a situation which is closer to the extreme case of full homogeneity across years than to the opposite extreme situation of fully heterogeneous relations across years.

Figure 4 plots the results of the estimation of the scale effect. The 3D plot (top panel) clearly indicates a nonlinear effect of pollution abatement capital. Again, three different patterns are observed. First, for very low levels of pollution abatement capital, a quite flat relation is generally highlighted but again there is a scarcity of data that makes any sound statistical interpretation rather difficult. Then, a bell-shaped function appears indicating that first the variance increases with pollution abatement capital, and then, after a threshold, a decreasing function appeared. Globally, this inverted U relation is rather asymmetric since the increasing part is quite gradual while the decreasing one is much more abrupt. This is also a relevant result indicating that initially, for low levels of pollution abatement capital, pollution investments makes slowly increase the variance of the unconditional efficiency scores, thus indicating an increase in the dispersion of the performances of firms, but after a threshold, more and more investments make such dispersion rather abruptly decreasing. Moreover, it can be also observed, that such a bell-shaped function seems becoming slightly more flat as time passes. As an additional insight, the marginal view from the perspective of time indicates that –when fixing pollution abatement capital to its median – the dispersion of the performances constantly slightly decreases overtime.

Figure 4

6 Summary and policy implications

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.

[8]For the unconditional efficiency score-pollution abatement capital relation, the marginal view simply refers to the median year, i.e. 2001.

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. We build on previous literature and precisely assume that pollution abatement investments are, at least partially, exogenously stimulated by environmental regulation.

A second novel aspect of this paper is its modeling 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.

Specifically, we adopt a three-step nonparametric approach. In a first step, nonparametric unconditional and conditional efficiency score estimates are obtained and used in an exploratory analysis. In a second step, we focus on the separability condition discussed in Simar and Wison (2007, 2011) and we adopt the recently proposed test by Daraio et al. (2017). In a last step, unconditional or conditional efficiency scores are regressed over pollution abatement capital, depending on the rejection or not of the separability condition in the previous step. In this last step, we estimate a location-scale nonparametric regression model, where cross-validation is used for the joint determination of the polynomial order and bandwidth.

The explanatory tools and the separability test provide us a first relevant result: pollution abatement capital does not seem to affect the boundary of the attainable set and the eventual effect on the production process is only through the distribution of the inefficiencies.

Then, the estimation of the location-scale model provides new and interesting results. Both the conditional expectation and the conditional variance of firms 'efficiencies are found to be related to pollution abatement capital with a nonlinear way, definitively indicating that the traditional paradigm according to which environmental regulation is a detrimental factor for firms' competitiveness and productivity and the Porter hypothesis may coexist. In particular, the first part of the relation seems to be consistent with the traditional view about environmental regulation, while the second one confirms the Porter hypothesis. Indeed, for low levels of pollution abatement capital, more investments make decrease the conditional expectation and increase the conditional variance. After a certain threshold, however, the opposite happens: more investments make increase the conditional expectation and decrease the conditional variance. These results also reinforce the view that firms' efforts to reduce pollution do not always positively affect their performances, but do in some cases. One rationale behind such relevant results could be linked to the existence of fixed costs and knowledge spillovers that may require a certain mass of investments to be effective. Understanding the economic mechanisms behind this result, which should be confirmed by other studies, is certainly the scope for future research. In addition, also time plays a role since overall it is found that the conditional variance of efficiencies slightly decreases overtime.

Overall, these are new results, which are also extremely relevant in terms of policy implications. A clear message emerges: a certain mass of pollution abatement capital is necessary in order to increase firms' efficiency; otherwise, pollution abatement investments will be detrimental for firms' economic performances.

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Appendix 1: Panel description

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.[9] 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

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

Appendix 2: Robustness checks

In the nonparametric location-scale kernel model, cross-validation is used for the joint selection of the smoothing parameters and the order of the local polynomial. This provided a local-constant approach for the location effect. As a robustness check, we estimated the location effect by à priori imposing the order of the local polynomial while choosing with cross-validation the bandwidths for z and t. Figure 7 plots the estimated function using either the local-linear or the local-quadratic approach. The resulting approximation is only slightly affected by such a choice and confirm the existence of a bell-shaped relation between inefficiencies and pollution abatement capital. This bell-shaped relation appears to be a robust result with our data.

Figure 7

Table 1: Summary statistics

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

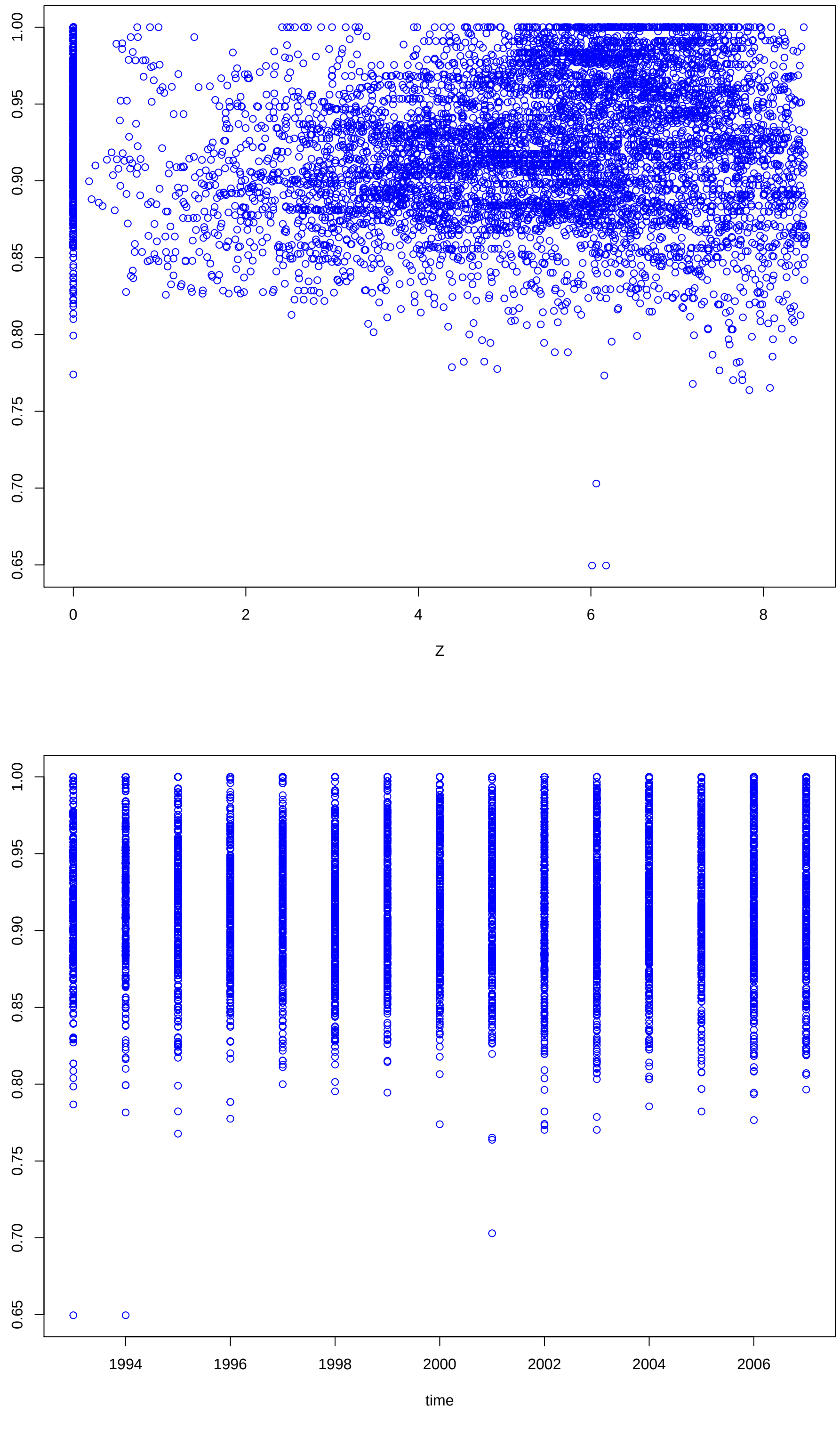


Figure 1: The top panel represents the full ratio $\widehat{R}_O(x, y|z, t)$ as a marginal function of pollution abatement capital (in logs). The bottom panel represents the full ratio $\widehat{R}_O(x, y|z, t)$ as a marginal function of time.

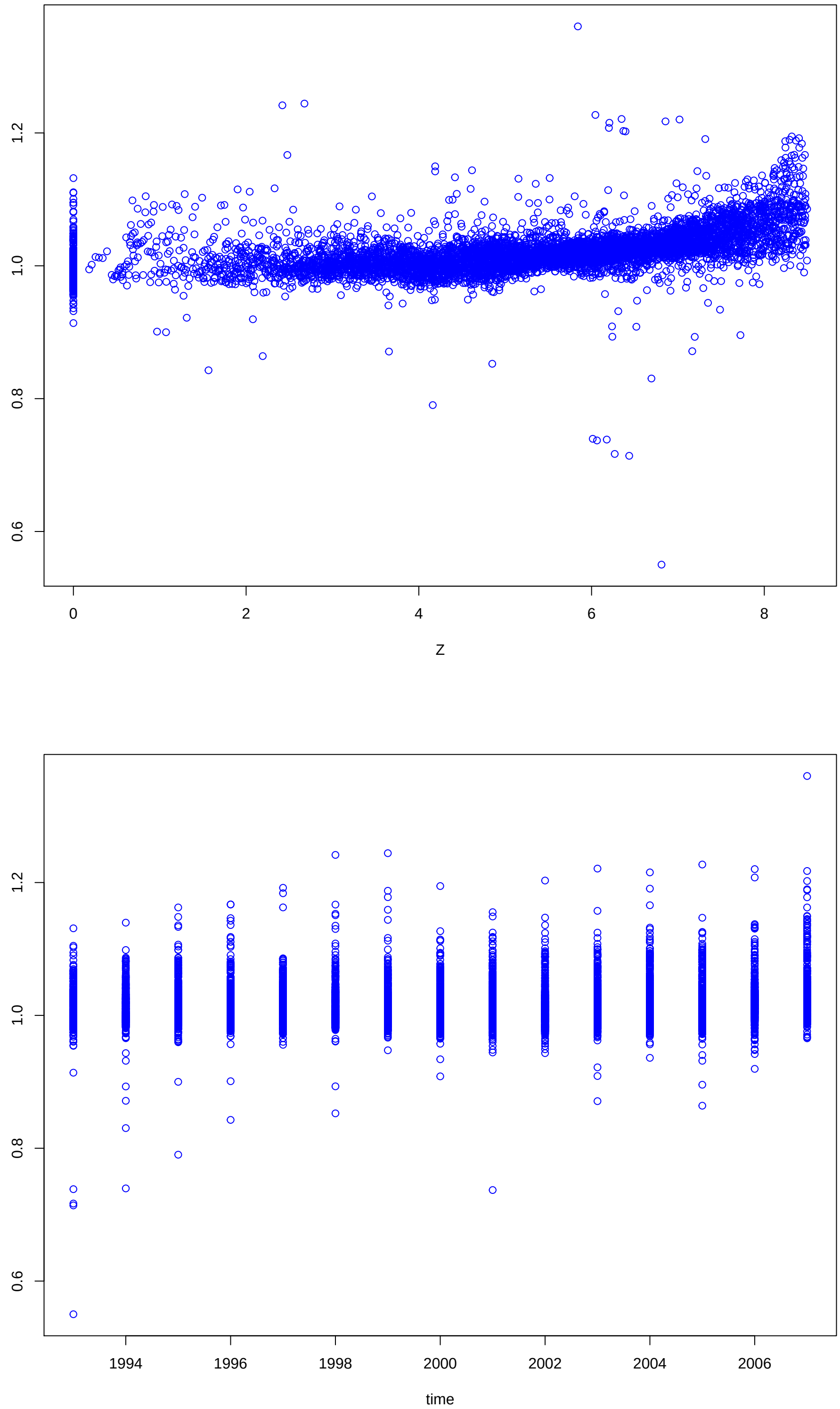


Figure 2: The top panel is the ratio $\widehat{R}_{O,\alpha}(x,y|z,t)$ for $\alpha = 0.5$, so for the median-order efficiencies, as a marginal function of pollution abatement capital (in logs). The bottom panel represents the ratio $\widehat{R}_{O,\alpha}(x,y|z,t)$ for $\alpha = 0.5$ as a marginal function of time.

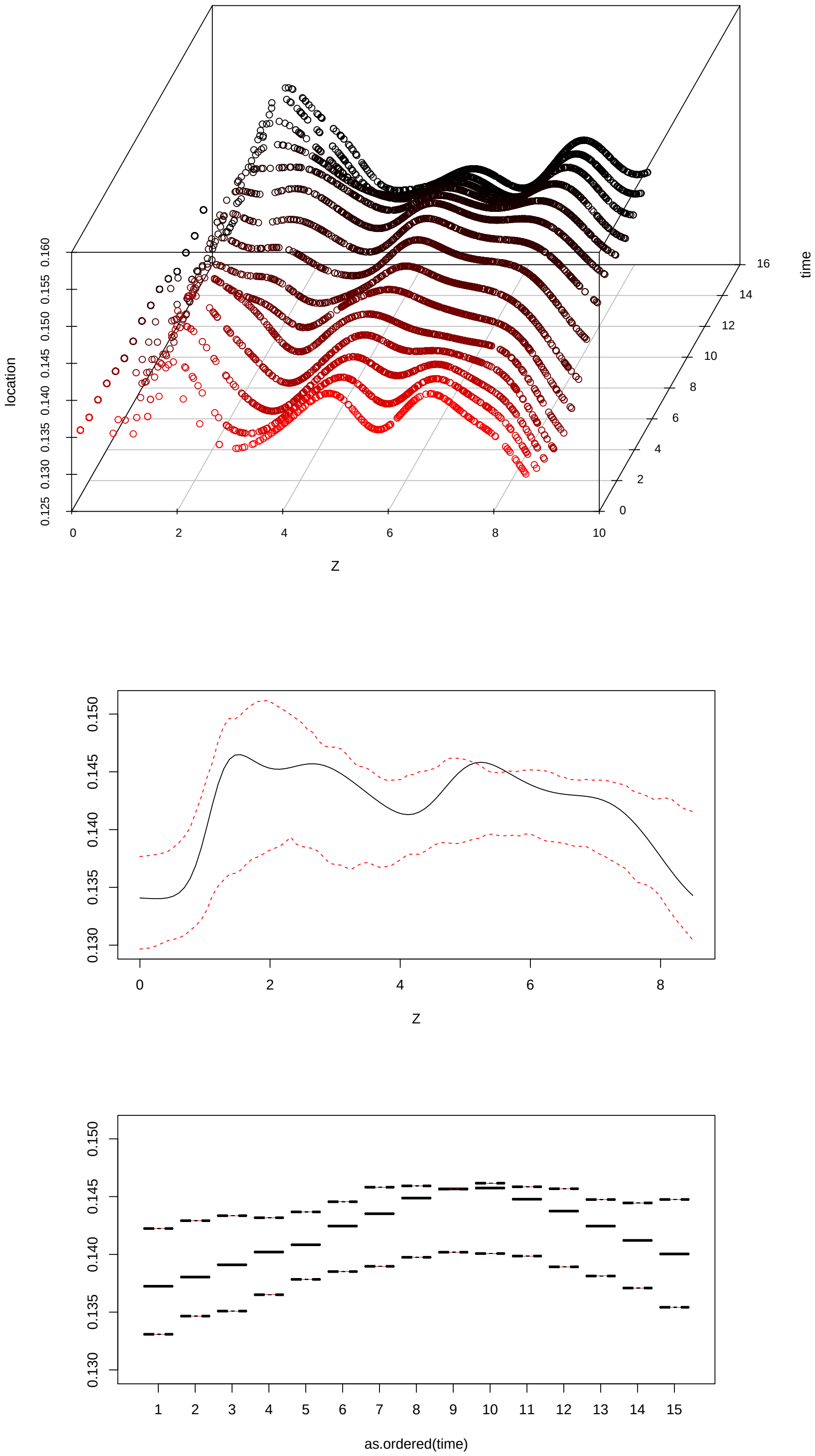


Figure 3: Estimated location effect of unconditional efficiency scores (top panel), and their two marginal views (bottom panel), as function of pollution abatement capital (in logs) and time. Generalized Local Polynomial Regression is employed. Here we use the $\log(\tau(x, y))$ as the dependent variable. The two marginal views are obtained by fixing the value of the other regressor to its median. 95% bootstrapped confidence bands are also reported.

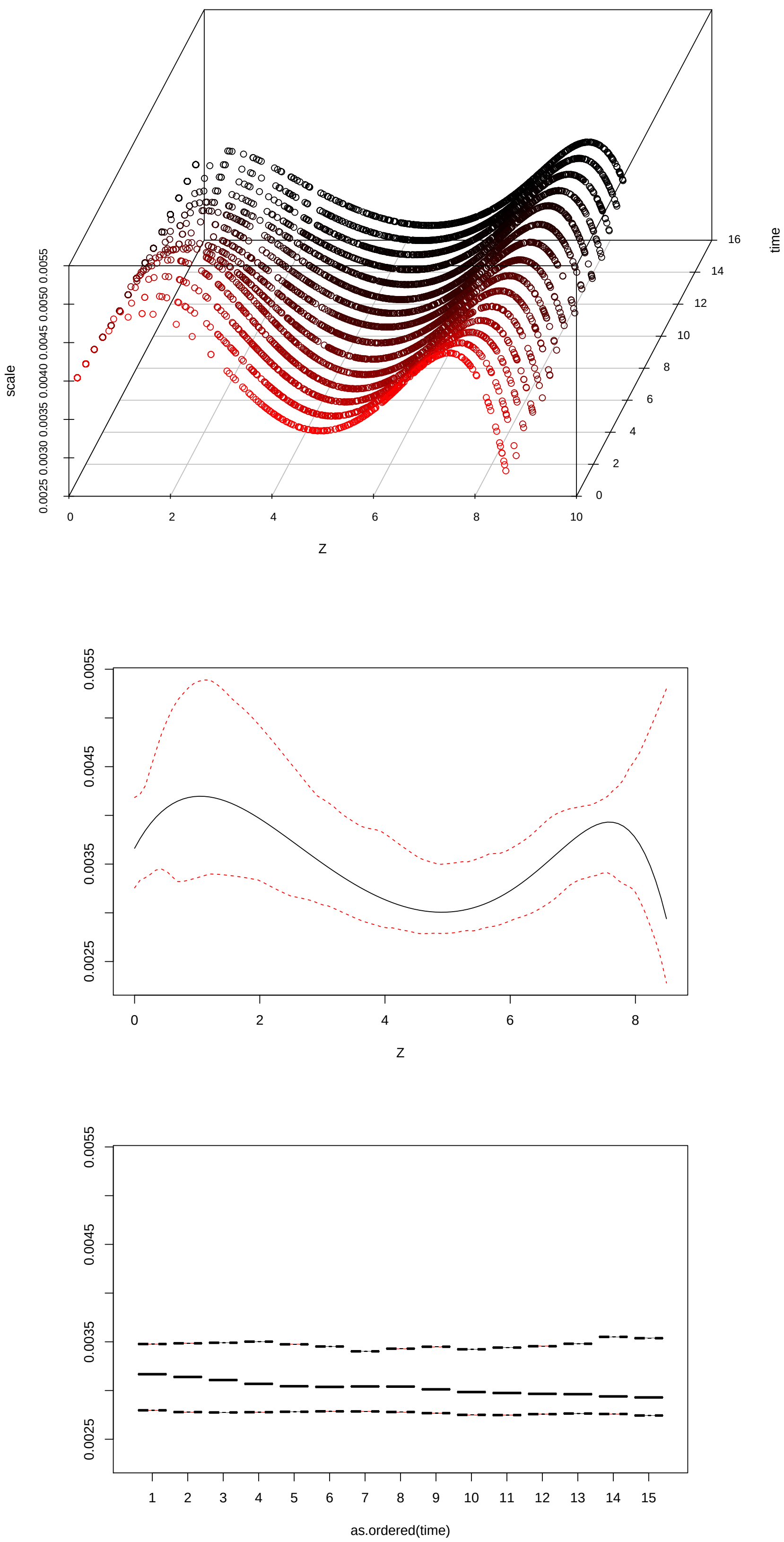


Figure 4: Estimated scale effect of unconditional efficiency scores (top panel), and their two marginal views (bottom panel). Generalized Local Polynomial Regression is employed. The two marginal views are obtained by fixing the value of the other regressor to its median. 95% bootstrapped confidence bands are also reported.

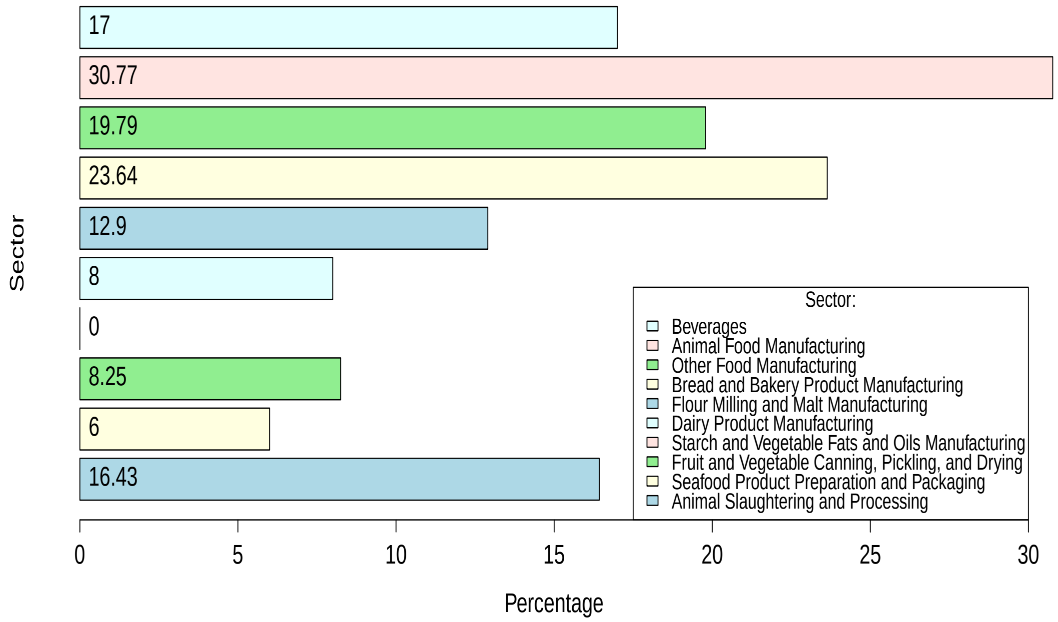


Figure 5: Percentages of pollution abatement non investing firms in food processing industry sectors

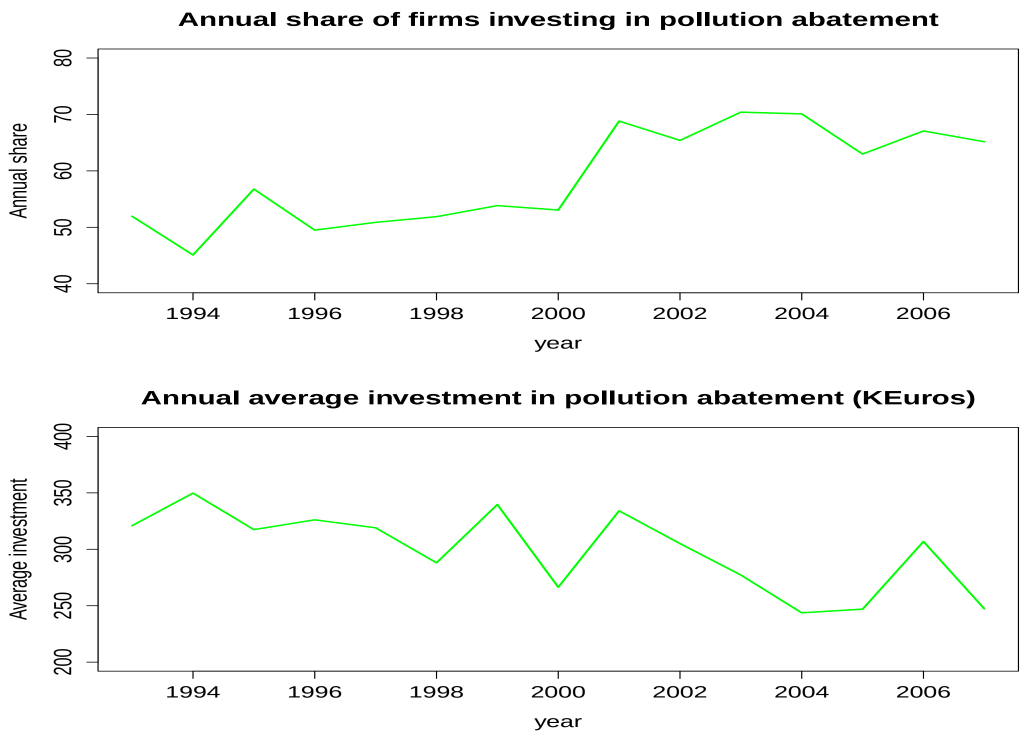
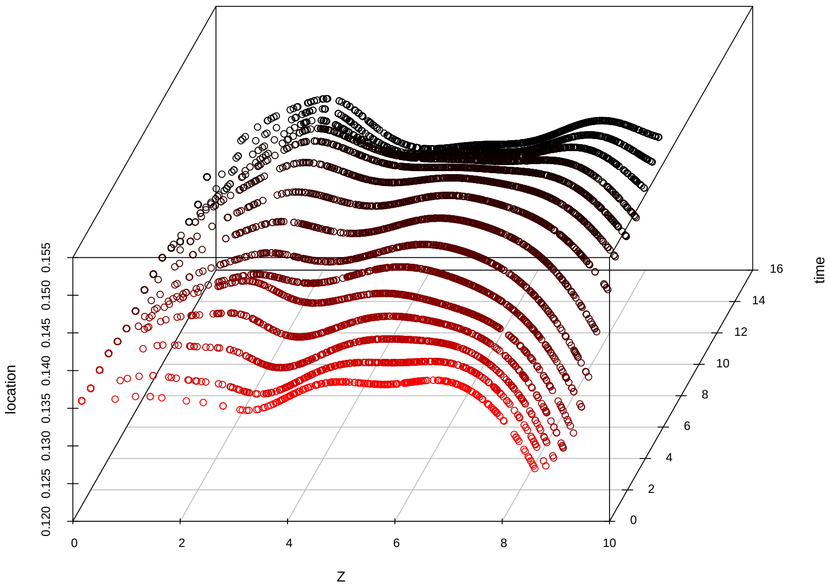


Figure 6: Trends in pollution abatement investments



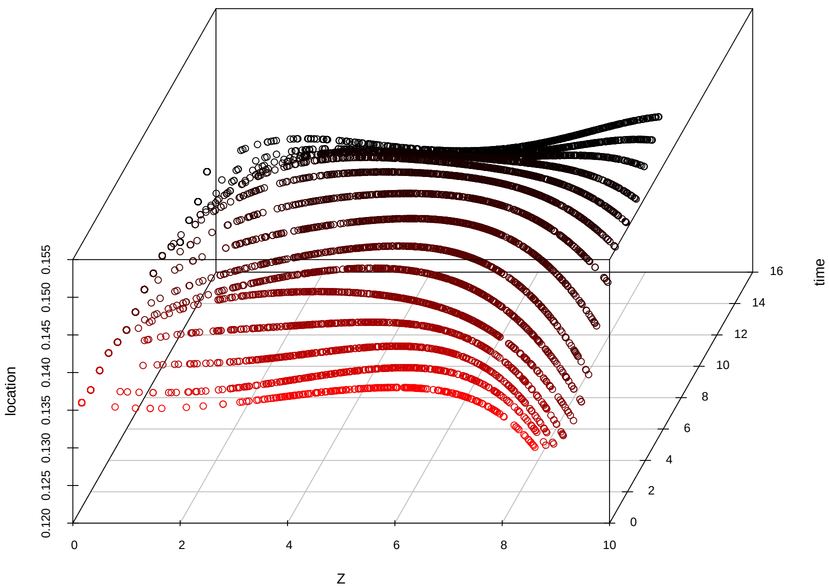


Figure 7: Estimated location effect of unconditional efficiency scores as function of pollution abatement capital (in logs) and time using the local-linear (top panel) and the local-quadratic (bottom panel) approach. We use the $\log(\tau(x, y))$ as the dependent variable.