The impact of pollution abatement investments on technology: Porter hypothesis revisited

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Abstract

This paper revisits the Porter hypothesis by pursuing two new directions. First, we compare the results obtained with two complementary approaches: parametric stochastic frontier analysis and conditional nonparametric frontier analysis. They presents relative advantages and drawbacks. Secondly, we pay attention not only on the average pollution abatement effort effect but we also focus on its variability across firms and over time. We provide new results suggesting that the traditional view about the effect of environmental regulation on productivity and the Porter hypothesis may coexist. This evidence supports the idea that a well-designed environmental regulation affects positively the firm performances *in some instances*.

JEL classification: C14, C23, D24, Q50.

Keywords: Porter hypothesis, pollution abatement investment, stochastic frontier analysis, time-varying efficiency, Vuong test, conditional nonparametric frontier analysis.

1 Introduction

Pollution clearly appears as an undesirable output of production. Because producing cleanly is more expensive than polluting, environmental regulation may be necessary in order to push 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 (see e.g. Viscusi, 1983, Jorgenson and Wilcoxen, 1990, Greenstone, 2002). From the early nineties, 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 they could enhance it. This new paradigm has become known as the "Porter hypothesis". Since then, such a hypothesis has received much attention. It has initially been criticized with respect to a lack of an underlying theory (e.g. Palmer *et al.*, 1995) and for being inconsistent with the empirical evidence (e.g. Jaffe *et al.*, 1995), while, today there exists a more solid theory but also a 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 empirical literature in two ways. First, with respect to an econometric modeling perspective, we aim to introduce in the Porter hypothesis literature some reasoning and modeling which have been recently developed by the econometric literature on productivity and efficiency analysis about the role of external factors of production. External variables are generally defined as variables that cannot, at least totally, be controlled by the producer but that may have an influence in the production process (see e.g. Bădin *et al.*, 2012). The available measures of firms' efforts to reduce pollution, such as pollution abatement investments, can be seen as such a kind of variables, being expected to be partially determined by environmental regulation. More precisely, we compare the results obtained with two approaches: parametric stochastic frontier analysis (SFA) and conditional nonparametric frontier analysis (CNFA). Both SFA and CNFA are suitable frameworks to account for external factors of production. These two approaches may be seen as complementary and comparing their results may be useful to provide a more nuanced and thorough picture of the effect of pollution abatement investments on technology. SFA has the relative advantage of having a well-developed statistical theory which allows for statistical inference. Hence, using SFA we can test alternative specifications as well as different hypotheses on the efficiency term and on all the other estimated parameters of the production frontier such as input elasticities, scale economies, efficiency, etc. It imposes, however, a, possibly restrictive or inconsistent, parametric specification. At the opposite, CNFA has the relative advantage over SFA that it does not make any assumptions, either about specific parametric functional form for the production frontier nor regarding distributional assumptions on the noise and inefficiency component. At the same time, however, a well-known problem with such an approach in the original formulation is its extreme sensitivity to outliers (Aigner and Chu, 1968; Timmer, 1971) which can cause a bias in the estimated production frontiers and efficiency measures and moreover the standard efficiency measures which can be obtained are point estimates and, therefore, it is not possible to construct standard errors and confidence intervals. New developments in nonparametric efficiency estimation overcome, at least partly, these limitations.

While most of the existing studies on the Porter hypothesis add the chosen proxy of pollution abatement efforts into a production function/ TFP equation as an additional factor of production, we follow the SFA literature modeling the impact of external factors either into the structure of the technology or into the technical efficiency. In particular, extending Coelli et al. (1999) we compare two models. In the first one, the pollution abatement effort enters as an additional input of production. This model encompasses the first model proposed by Coelli et al. (1999) where the external factor influences the shape of the technology. The second one assumes that pollution abatement effort affects the degree of technical inefficiency (see also Greene, 2005, for a description of such a kind of models). Since these two models are not nested, we then perform the Vuong (1989) test in order to select the most likely one.

Concerning the CNFA, we follow recent developments in the related literature (Cazals et al., 2002; Daraio and Simar, 2005; Bădin et al., 2012, Mastromarco and Simar, 2014), to disentangle the potential effects of conditioning variables (in our case pollution abatement investment) and identify effects on the boundary (shape of the frontier) and effects on the distribution of the inefficiencies in a full non-parametric setup. The first effect can be investigated by considering the ratios of conditional to unconditional efficiency measures, which are measures relative to the full frontier of respectively, the conditional and the unconditional attainable sets. The second effect of pollution abatement investments on the distribution of the inefficiencies can be investigated by looking at the so-called order-α median quantile efficiency measures.

A second novel aspect of this paper is its empirical and policy oriented perspective since we focus on one relevant aspect of the Porter hypothesis which has been neglected by the existing empirical literature. Indeed, as also stressed by Ambec *et* *al.* (2013), the Porter hypothesis does not say that properly designed environmental regulations always enhance firms' performance but it says that they do *"in some instances"*. We thus pay attention not only on the average pollution abatement effort effect but also focus on its variability across firms and over time. These two contributions allow us to provide new insights on the Porter hypothesis literature.

In order to perform the econometric analysis, we build on a new and rich firm-level panel data set concerning the French food processing industries and covering the period 1993-2007, the French food processing industry being particularly relevant for such a kind of analysis. The Food industry is not only relevant in terms of size, representing in France a large part of manufacturing, (about 550,000 employees in 2011, i.e. 18% of manufacturing employment) but is also relevant because it is one of the most polluting sector with respect to several indicators, especially when looking the effects of total final consumption of the produced goods (European Environmental Agency, 2006). This has been shown by several studies. Marin *et al.* (2012) using the NAMEA (National Accounting Matrix with Environmental Accounts) data show that food and especially animal-based food productions have a dominant role in the total environmental impact by consumption. Vieux *et al.* (2012) note that the contribution from the food processing industries to the total green house gas emission range from 15 to 31%. Moreover, in 2007, the food processing industry was found to be the third greatest spender on pollution abatement investments in France (167 million €), only exceeded by the energy (437 million €) and chemicals, rubbers and plastics (204 million €) industries.

The estimation results provide some relevant insights. First, concerning the parametric approach, the model selection procedure indicates that the model where the pollution abatement capital enters the production process as an input is preferred to the model where such a variable affects the inefficiency. Secondly, while the average pollution abatement capital elasticity equals 0.018, its estimated density is bimodal, with a negative and a positive mode. Moreover, the area under the density for positive values of the elasticity is greater than the same area for negative values, indicating that most firms have a positive elasticity while a small number of firms have a negative one. Third, we document a positive shift of both pollution abatement capital elasticity and efficiency over time. Forth, concerning the elasticities of substitution, while pollution abatement capital is always substitute with labour, it appears to be substitute with physical capital only for a fraction of the firms, the substitutability between these two factors increasing constantly over the period. Finally, the conditional nonparametric approach fully confirms the above presented results and provides additional insights. It indeed suggests the existence of an effect of pollution abatement capital on the shape of the frontier but not globally on the distribution of the efficiency. More precisely, it indicates a nonlinear inverted U effect on the shape of the frontier and a very flat relation, but with a positive relation for the highest values of pollution abatement capital, when looking at the partial frontiers. These result clearly complements the bimodal estimated density of pollution abatement elasticity and the positive but not significant effect of pollution abatement capital on firms' efficiency documented adopting a translog stochastic frontier.

Summarising, to the best of our knowledge, this is the first empirical paper suggesting that the traditional view about the effect of environmental regulation on productivity and the Porter hypothesis may coexist and supporting the idea that a well-designed environmental regulation affects positively the firm performances *"in some instances"*.

The present paper is organized as follows. Section 2 gives a brief review of the related literature. Sections 3 and 4 present the econometric methodologies while the description of the data and some descriptive statistics are provided in section 5. Section 6 details the results and section 7 concludes.

2 Related literature

With respect to the specific goal of the paper, it seems worth discussing and linking two separate literatures.

2.1 Environmental regulation and economic performance

According to a standard view among economists, at least until the nineties, pollution abatement effort due to environmental regulation may be benefic for environmental performance but would negatively affect the firms' economic performances since it forces firms to allocate the production inputs to pollution reduction, which pushes them away from the optimal production choices. This in turn could lead firms to delay their investments (Viscusi, 1983) or relocate their activities in countries imposing less stringent pollution regulations (Greenstone, 2002). At the national level, Jorgenson and Wilcoxen (1990) suggest that environmental regulation explains part of the sharp decline in the rate of economic growth during the 1970's and 1980's.

From the early nineties, 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) indeed 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 (for a recent survey, see e.g., Ambec *et al.* 2013). From a theoretical point of view, after some initial criticisms (e.g. Palmer *et al.*, 1995), the literature has provided alternative argumentations supporting such a hypothesis. These are firms' behaviors departing from the assumption of profit maximization (e.g., Ambec and Barla, 2006), market failure (e.g., André *et al.*, 2009), organization failure (e.g., Ambec and Barla, 2002) and R&D spillovers (e.g., Mohr, 2002).

Empirically, Jaffe and Palmer (1997) first distinguished among the "weak" and the "strong" version of the Porter hypothesis. According to the weak version, properly designed environmental regulation may stimulate innovation. This is has been validated by many previous studies (Lanjouw and Mody, 1996, Jaffe and Palmer, 1997, Brunnermeier and Cohen, 2003, Popp, 2006, Arimura *et al.*, 2007). The strong version makes a step further suggesting that in many cases this innovation more than offsets the regulatory costs, in the end enhancing firms' competitiveness and economic performances (most often measured with the firms' productivity). For this respect, while most of the studies reviewed by Jaffe *et al.* (1995) find a negative effect of environmental regulation on productivity and firms' performances, some more recent works suggest a positive effect (see e.g. Berman and Bui, 2001, Alpay *et al.*, 2002, Yang and Yao, 2012). In summary, while there is a well established consensus on the weak version, the empirical evidence on the strong version is much more mixed and requires further investigations.[1]

2.2 Accounting for external factors

The second strand of the literature which is relevant for this paper is that focusing on external (or environmental) factors.[2] External factors may be broadly defined as *"External or environmental factors that cannot be controlled by the producer but may influence the production process"* (Bădin *et al.*, 2010, Mastromarco and Simar,

[1]Some recent works study simultaneously both the weak and the strong versions (e.g., Hamamoto, 2006, Lanoie *et al.*, 2011, Van Leeuwen and Mohnen, 2013).

[2]Hereafter we refer to external factors to avoid confusion with the environment, defined in terms of ecological units and natural resources.

2014). Concerning more generally the production process, it has been also suggested that *"producer performance is influenced by three very different phenomena: the efficiency with which management organizes production activities, the characteristics of the environment in which production activities are carried out, and the impact of good and bad luck, omitted variables, and related phenomena which would be collected in a random error term in a regression-based evaluation of producer performance. The first phenomenon is endogenous, while the second and third are exogenous."* (Fried *et al.*, 2002).

Both SFA and CNFA provide a useful framework to deal with this issue. Within the former framework, Battese and Coelli (1995) introduced a class of model where the external factors influence directly the inefficiency, while Greene (2005) suggested adopting the least restrictive variant of the Battese and Coelli model. Coelli et al. (1999) propose testing the Battese and Coelli (1995) model against a more conventional specification where the external factors are supposed to affect the shape of the production technology. The subsequent literature has used the Battese and Coelli (1995) model in many and diversified contexts such as the efficiency of universities (Kempkes and Pohl, 2010), the productive efficiency of developing countries (Henry et al., 2009, Mastromarco and Ghosh, 2009), the effect of the business environment on inefficiency (Roudaut, 2006), just to cite few recent papers. Parametric methods however require strong assumptions on the specification of the production function and distribution on the error components. If these assumptions are not supported by the data under analysis, the estimates and inference will be flawed and the nonparametric methods will give more reliable results. Recently, nonparametric estimators of production function and efficiency to model the effect of external factors on production process have been developed (Cazals et al. 2002, Daraio and Simar 2005, Bădin et al. 2012 and Mastromarco and Simar 2014).

With respect to the role of pollution abatement efforts, almost all the existing studies add the chosen proxy for pollution abatement efforts as an additional explanatory variable in a parametric production function / total factor productivity equation without testing such specification against some possible alternative. To the best of our knowledge, Broberg et al. (2013), adopting the Battese and Coelli (1995) approach, is the sole work introducing pollution abatement investments as a determinant of technical inefficiency while there are not attempts to use nonparametric frontiers to analyse the effect of pollution abatement efforts on technology. Starting from this state of the art, this paper aims to provide new methodological and policy oriented insights by testing alternative parametric specifications and also considering conditional nonparametric frontiers.

3 Stochastic frontier analysis

The most common approaches in the SFA literature model the impact of external factors either into the structure of the technology or into the technical efficiency (see e.g. Coelli *et al.*, 1999). We follow and extends these trends and consider two alternative models to include pollution abatement capital, Z_{it}, into the production process.

3.1 Input model

In the first model, we extend Coelli *et al.* (1999) by assuming that Z_{it} enters a stochastic frontier production function as an additional factor of production (we label this model to as *input model)*:

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

where the output of a firm i at time t, Y_{it}, is determined by the levels of labour input and physical capital, L_{it} and K_{it}. It is also affected by pollution abatement capital, Z_{it}, while t captures technological change over time. The w_{it} are assumed to be independent and identically distributed random errors, which capture the stochastic nature of the frontier while τ_{it} denotes efficiency with $0 < \tau_{it} \leq 1$. When $\tau_{it} = 1$, the firm produces on the efficient frontier.

A maintained hypothesis along the paper is that the technology has a translog form with non neutral technological progress. The translog form can be interpreted as a second order Taylor series approximation of an unspecified underlying production function and achieves local flexibility (also called Diewert flexibility) implying that the approximating functional form provides perfect approximation for the underlying function and its first two derivatives at a particular point (Fuss *et al.,* 1978). It has also been shown that it outperforms other Diewert-flexible forms (Guilkey *et al.,* 1983). Equation (1) can be written as:

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

where lower case letters indicate variables in natural logs, i.e., $y_{it} = \ln(Y_{it})$, and so on, $u_{it} = -\ln(\tau_{it})$ is a non-negative random variable, and $v_{it} = \ln(w_{it})$, distributed as $N(0, \sigma_v)$. It is worth to note that we do not exclude, *a priori*, the possibility that pollution abatement capital enters the production function as a production inputs rather than restricting its effect to the shape of the technology as in Coelli *et al.* (1999). This, for two reasons. First, we cannot exclude that such variable can be assimilated to a production input which is under the control of the producer choosing the optimal level of pollution abatement investment given some external constraints (such as environmental regulation) and within its maximization program. Say differently, it appears difficult to exclude ex-ante the possibility that pollution abatement capital acts as an input having a full effect on technology, e.g. also in terms of elasticity of substitution, even if its level could be determined taking into account environmental regulation and other external constraints. Secondly, this model nests the model estimated by Coelli *et al.* (1999) which assumes that external variables affect only the shape of the production technology, and can be easily tested by imposing the following restriction:

$$\gamma_z = \delta_{\tau z} = \delta_{kz} = \delta_{lz} = 0 \tag{3}$$

The inefficiency term u_{it} can be modelled as a time invariant truncated-normal random variable, i.e. $u_{it} = u_i$ and $u_i \overset{iid}{\sim} TN\left(\mu, \sigma_u^2\right)$. The time invariance of the inefficiency component is, however, a problematic assumption. One multiplicative form which has been proposed consists of variations on:

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

where $u_i \overset{iid}{\sim} TN\left(\mu, \sigma_u^2\right)$. Concerning $\ell(t,T)$, we consider a variant of the Battese and Coelli (1992) model, as proposed by Greene (2005) which can be written as:

$$\ell(t,T) = \exp(\sum_{t=2}^{T} \gamma_t d_t) \tag{4}$$

where d_t denote year dummies.[3] The time invariance can be relaxed also by con-

[3]By construction, a constant term in eq. (4) 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

sidering a second specification, which we label as additive (see e.g, Battese and Coelli, 1995, Coelli *et al.*, 1999), for the inefficiency:

$$u_{it} \overset{iid}{\sim} TN\left(\mu_{it}, \sigma_u^2\right), \text{ with } \mu_{it} = \mu + \sum_{t=2}^{T} \gamma_t d_t \tag{5}$$

The two specifications (eqs. 4 and 5) differ in the way they model time-varying inefficiency. In the multiplicative model (eq. 4) the underlying truncated normal variable u_i is scaled by the exponential function of time. The inefficiency component in this model varies in the systematic way with respect to time.[4] The other inefficiency model (eq. 5) is Battese and Coelli (1995) specification. This is a pooled model where the time variation of inefficiency depends on the way the time affects the mean of truncated distributed variable u_{it}.

3.2 Efficiency model

An alternative model (see, e.g., Battese and Coelli, 1995, Coelli *et al.*, 1999; Kempkes and Pohl, 2010, Henry *et al.*, 2009, and Roudaut, 2006) assumes that pollution abatements capital affects the technical efficiency (hereafter, *efficiency model*):

$$Y_{it} = F(t, K_{it}, L_{it})\tau_{it}(Z_{it})w_{it}. \tag{6}$$

By writing equation (6) in translog form we have:

$$\begin{aligned} y_{it} = {} & \alpha + \beta_\tau t + \beta_k k_{it} + \beta_l l_{it} + \gamma_\tau \frac{t^2}{2} + \gamma_k \frac{k_{it}^2}{2} + \gamma_l \frac{l_{it}^2}{2} + \delta_{\tau k} t k_{it} + \delta_{\tau l} t l_{it} + \delta_{kl} k_{it} l_{it} + \\ & - u_{it} + v_{it} \end{aligned} \tag{7}$$

is set to zero.

[4]Greene (2005) defines this model 'time dependent' rather than time variant inefficiency model.

where v_{it} is the usual random error term, i.e. $v_{it} \overset{iid}{\sim} N(0, \sigma_v^2)$. We consider two alternative specifications for the inefficiency term u_{it}, a multiplicative one and an additive one, as for the input model. The multiplicative model can be written as:

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

where

$$u_i \overset{iid}{\sim} TN\left(\mu, \sigma_u^2\right) \text{ and } \ell(t, T, Z_{it}) = \exp(\sum_{t=2}^{T} \gamma_t d_t + \theta Z_{it}), \tag{8}$$

while the additive model can be written as:

$$u_{it} \overset{iid}{\sim} TN\left(\mu_{it}, \sigma_u^2\right) \text{ and } \mu_{it} = \mu + \sum_{t=2}^{T} \gamma_t d_t + \theta Z_{it} \tag{9}$$

In summary, 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. They are estimated by maximum likelihood. Since they are non nested, in order to choose the most preferred specification, we perform the modified likelihood-ratio test proposed by Vuong (1989) to compare non-nested models.[5]

4 Conditional Nonparametric Frontier Analysis

Following recent developments in nonparametric frontier literature (Cazals et al., 2002; Daraio and Simar, 2005; Bădin et al., 2012, Mastromarco and Simar, 2014), we can disentangle the potential effects of conditioning variables (in our case pollution

[5] Appendix 1 recalls the definition of this test.

abatement capital) to identify effects on the boundary (shape of the frontier) and effects on the distribution of the inefficiencies in a full nonparametric setup.

We recall first the probabilistic formulation of a production process introduced by Cazals et al. (2002). This formulation does not take into account the existence of external factors. Thus, let $X \in \mathbb{R}_+^p$ and $Y \in \mathbb{R}_+^q$ denote the vector of inputs and the vector of outputs, respectively. The production process can be described by the probability measure of variables (X, Y) on $\mathbb{R}_+^p \times \mathbb{R}_+^q$ defined as

$$\begin{aligned} S_{X,Y}(x,y) =& Prob\,(X \leq x, Y \geq y) \\ =& S_{Y|X}(y|x) \times F_X(x) \end{aligned} \tag{10}$$

In other words, the function $S_{X,Y}(x,y)$ is the probability for a unit (x,y) to be dominated by other production units. This probability can be decomposed as the product of $S_{Y|X}(y|x)$ which is the conditional survival function of Y given that $X \leq x$, and $F_X(x)$ which is the cumulative distribution function of X. It can be easily shown that the support of $S_{X,Y}(x,y)$ defines Ψ, the attainable production set. Output-oriented Farrell-Debreu technical efficiency for a production unit characterized by $(x,y) \in \Psi$ can then be computed as

$$\tau(x,y) = \sup\{\tau | (x, \lambda y) \in \Psi\} = \sup\{\tau | S_{Y|X}(\tau y|x) > 0\}, \tag{11}$$

Output-oriented Farrell-Debreu technical efficiency measures defined by equation (11) are known to be sensitive to the presence of outliers or extreme values. Robust order-α quantile efficiency measures were introduced by Daouia and Simar (2007). They are defined for any $\alpha \in (0, 1)$ as follows.

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

so we are defining the support of Y under the conditioning at a less extreme quantile (unless $\alpha = 1$), which allows us to estimate more robust efficiency measures not influenced by extreme or spurious observations.

The probabilistic framework introduced by Cazals et al. (2002) can be generalized to account for the existence of external factors as follows. Let $Z \in \mathbb{R}^d$ denote the vector of external variables. Consider now the conditional probability measure of triple variables (X, Y, Z) on $\mathbb{R}_+^p \times \mathbb{R}_+^q \times \mathbb{R}^d$ defined as

$$\begin{aligned} S_{X,Y|Z}\,(x, y|z) =& Prob\,(X \leq x, Y \geq y|Z = z) \\ =& S_{Y|X,Z}\,(y|x, z)\,F_{X|Z}\,(x|z) \end{aligned} \tag{12}$$

$S_{X,Y|Z}\,(x, y|z)$ represents the probability for a production unit (x, y) to be dominated by other production units experiencing the same external conditions z, and its support defines Ψ^z, the attainable production set when $Z = z$. Conditional output-oriented Farrell-Debreu technical efficiency and conditional robust order-α quantile efficiency measures can now be defined as

$$\begin{aligned} \tau(x, y|z) &= \sup\{\tau|S_{Y|X,Z}(\tau y|x, z) > 0\} \text{ and} \\ \tau_\alpha(x, y|z) &= \sup\{\tau|S_{Y|X,Z}(\tau y|x, z) > 1 - \alpha\}. \end{aligned}$$

As stated in Bădin et al. (2012), by using small values of α, it is possible to analyze the distribution of the inefficiencies and to assess the influences of the external variables Z in the interior of the attainable sets Ψ and Ψ_t^z. The effect of the external variables 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 sets:

$$R_O(x, y|z) = \frac{\tau(x, y|z)}{\tau(x, y)}. \tag{13}$$

The second effect of Z, on the distribution of the inefficiencies, can be investigated by looking to order-α quantiles efficiency measures (Daouia and Simar, 2007). The full frontier corresponds to an extreme quantile, i.e. the maximum achievable output, but we will look here to more central quantiles. For our purpose of analyzing the impact of Z on the distribution of efficiencies, we are interested in the median, by choosing $\alpha = 0.50$. The ratios to be analyzed are now

$$R_{O,\alpha}(x, y|z) = \frac{\tau_\alpha(x, y|z)}{\tau_\alpha(x, y)}. \tag{14}$$

For the output orientation, when the ratios (13) are globally increasing with Z, this indicates an favourable effect on the production process. On the contrary, when these ratios are globally decreasing with Z, we have an unfavourable effect of Z on the production process. As explained in Bădin et al. (2012), the full frontier ratios (13) indicate only the effect of Z on the shape of the frontier, whereas with the partial frontiers (14) this effect may combine effects on the shape of the frontier and effects on the conditional distribution of the inefficiency. 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 conditioning variable Z changes; if the effect with the medians is more important than for the full frontier, this indicates that in addition to an effect on the shape of the frontier, we have also an effect on the distribution of the efficiencies.[6] In practice we use nonparametric estimators of the efficiency

[6]See Figure 10, in Bădin et al., (2012) for a detailed explanation of the different possible

measures[7] and we explore the effect of Z by looking to the behaviour of $\widehat{R}_O(x, y|z)$ and $\widehat{R}_{O,\alpha}(x, y|z)$ as a function of z.

5 Data

Plant-level 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. It covers plants with at least 100 employees. To our knowledge, this paper represents the first attempt to use this survey for academic purposes. The ANTIPOL survey provides information on pollution abtements investments defined as *"the purchase of buildings, land, machinery or equipment to limit the pollution generated by the production activity and the internal activities or the purchase of external services improving the knowledge to reduce the pollution"*. This plant-level measure of pollution abatement investments is aggregated at the firm-level and the firm-level pollution abatement capital stock is built using the perpetual inventory method using a depreciation rate of 15%. This is a standard rate adopted in the literature for investments in pollution abatement (Aiken *et al.*, 2009).

The EAE is a firm-level survey covering almost all firms with 20 or more employees. It provides a measurement for the value-added, deflated by its annual industry price index and for the standard inputs of production, labour measured with the number of firm employees by annual average in full-time equivalents, and capital measured with the amount of fixed assets deflated by the annual price index for

scenarios.

[7]Conditional and unconditional efficiency measures can be estimated using nonparametric methods such as DEA (Data Envelopment Analysis) or FDH (Free Disposal Hull) (see Bădin et al., 2012).

equipment goods.

The two data bases are merged providing us the variables we need to estimate a production function. In order to make the merge, the plant-level data obtained from the ANTIPOL survey have been aggregated at the firm level, in the end obtaining an unbalanced panel data set composed of 8391 observations and 1130 firms observed during the 1993-2007 periods.

Table 1 presents some descriptive statistics for the variables used to estimate the production function: value added, labour (number of workers), physical capital stock, and pollution abatement capital stock.[8] This table shows that average pollution abatement capital stock is about one-fiftieth of average physical capital stock. Since 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 behaviours across sectors, making the dummy D redundant. The same definition, $z \equiv \ln(Z + D)$, is also adopted when focusing on the conditional nonparametric frontier.

[8]Appendix 2 gives a more detailed description of the panel.

Variable	Label	Mean	Std. dev.	Min	Max
Value-Added (K Euros)	VA	27605.71	52847.71	100.16	609216
Labour (Number of workers)	L	418.03	534.38	100	6677
Capital stock (K Euros)	K	47756.40	104830.80	.5	2314025
Pollution Abatement Capital stock (K Euros)	Z	980.53	2575.60	0	41456.53

Table 1: Summary statistics

6 Results

6.1 Model selection

We start with the SFA and estimate the four parametric specifications proposed above.[9][10] Then we perform the Vuong test in order to select the most likely model. Results are reported in Table 2. First, Vuong tests clearly indicate that the multiplicative specification of efficiency is preferred to the additive specification, for both the input and efficiency models. Signs of the Vuong test statistics are negative and p-values are very small. Second, Vuong test shows that the input model is preferred to the efficiency model when comparing them in the multiplicative case. Sign of the test statistics is positive and the associated p-value is much smaller than usual significance levels. To sum up, we select the multiplicative input model as the most likely model at the result of the model selection procedure.

It is also interesting to note that the input model not only appears to be more likely than the efficiency model but also that in the latter, the estimate of the parameter associated to pollution abatement capital, θ from equation (6), is negative (this would suggest a positive effect on efficiency), but also it is close to zero ($-0.419e-5$) and is far to be significant at standard levels ($p-value = 0.307$).

[9]Sectorial fixed effects have been included in the translog specification. These sectorial dummies account for unobserved environmental and technological factors that have different effects on production in different sectors.

[10]Detailed results are available upon request to the authors.

Table 2: Model selection results

Null Hypothesis	Vuong Test Statistics	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

We then proceed to a test of 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 defined by equation (3). The likelihood ratio test statistics whose value is 18.616 with a p-value equals to 0.001, allows us to reject such an hypothesis. Pollution capital abatement enters the production function as an input.

These results have relevant policy oriented implications, indicating that environmental policies aimed to push firms to invest to reduce pollution do not simply shift the shape of the production function or the firm's efficiency but they full affect the technology of the firms.

6.2 Elasticities

The estimated values of the parameters of the preferred model, i.e. the multiplicative input model, allows computing the output elasticities with respect to the inputs. These elasticities vary across firms and over years. Figure 1 gives their estimated densities using nonparametric kernel estimators. On average, capital and labour elasticities are equal to 0.255 and 0.780 respectively.

One of the main result of the paper is given by the estimated density of pollution abatement capital elasticity. It is worth noting that while the average pollution

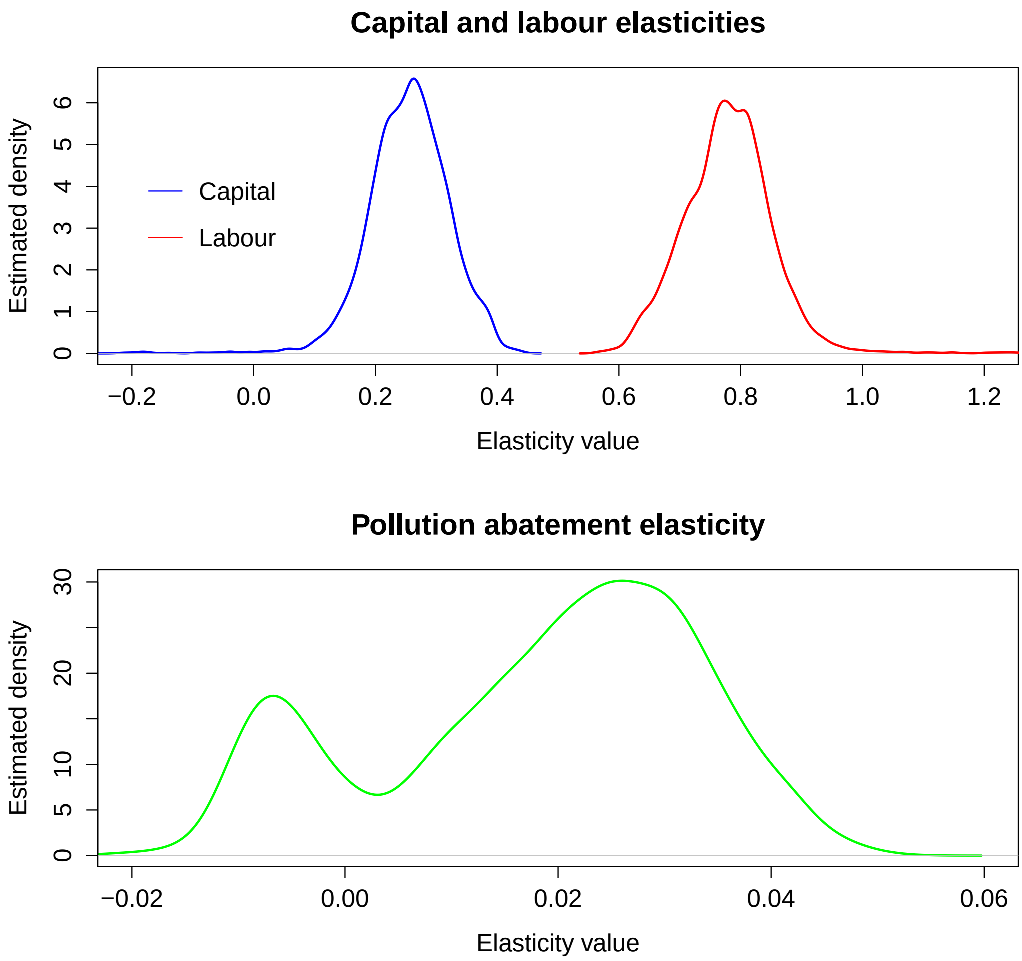

Figure 1: Estimated densities of elasticities

abatement capital elasticity is equal to 0.018, the density is bimodal. This density appears to be a mixture of two underlying densities, a first one with a negative mode and a second one with a positive mode. Moreover, the area under the density for positive values of the elasticity is greater than the same area for negative values, indicating that most firms have a positive elasticity while a small number of firms have a negative one. 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 a well-designed environmental regulation does not always affect positively the firm performances, but it does in many cases, as also stressed by Ambec *et al.* (2013).

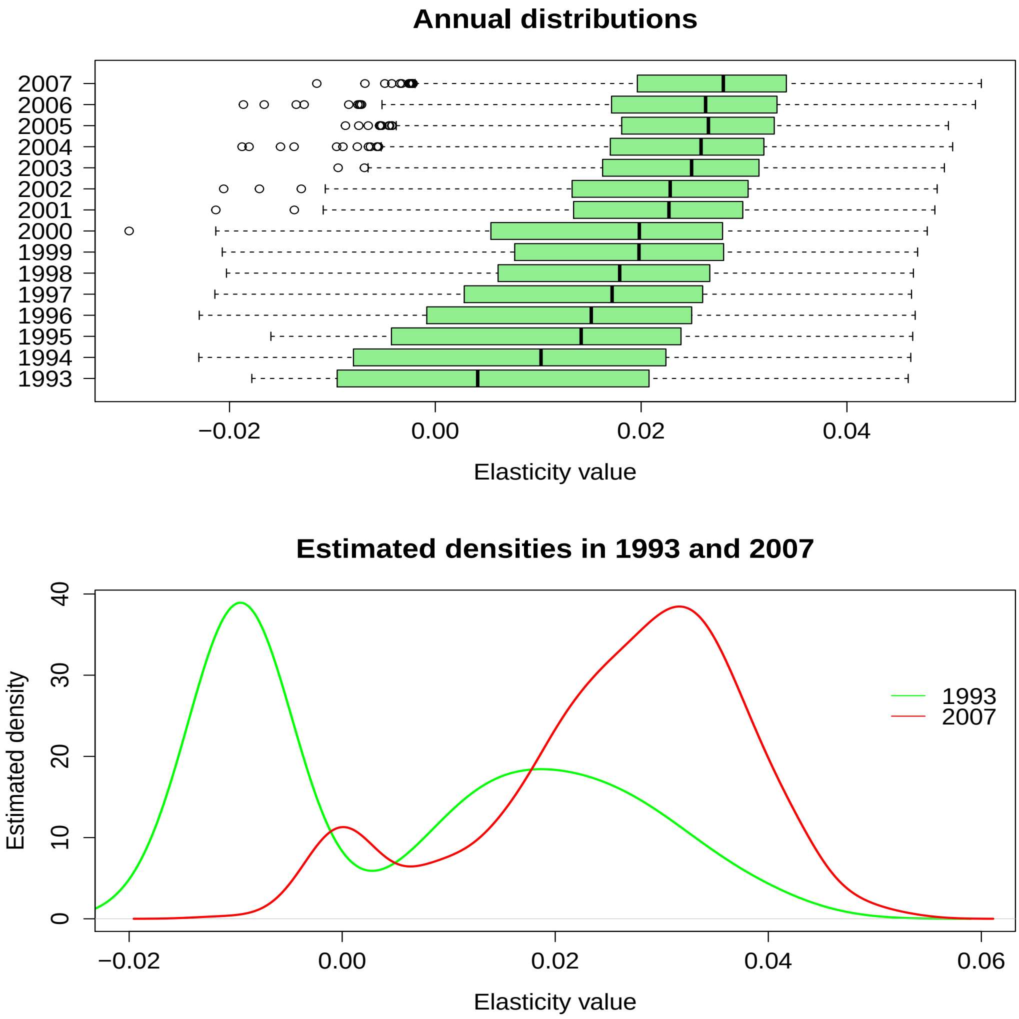

Figure 2: Evolution of pollution abatement elasticity distributions over time

A closer look at the annual distributions of pollution abatement elasticities (see figure 2) shows a positive trend. The median increases over time from 0.004 in 1993 to 0.0280 in 2007. The interquartile range decreases over time, and the annual distributions of elasticities shrink, the standard deviation decreasing from 0.017 in 1993 to 0.012 in 2007. Less and less of firms exhibit a negative pollution abatement elasticity. The comparison of the estimated densities in 1993 and 2007 strengthens this view. The two densities are always bimodal. Nevertheless, there is a shift from

1993 to 2007. Almost all firms have a positive elasticity in 2007 while the number of firms with positive elasticity is roughly the same as the number of firms with a negative one in 1993. Moreover, the first mode moves from -0.011 in 1993 to about zero in 2007. To sum up, this result reinforces the idea that a well-designed environmental regulation does not always affect positively the firm performances, but it does in many cases and we observe that this positive effect concerns an increasing over time number of firms.

The comparison with previous works is not straightforward since they provided very mixed evidence about the sign of the effect of pollution abatement effort on productivity and, at the same time, this paper represents to the best of our knowledge the first work focusing on the heterogeneity across firms and over time of the estimated elasticity of pollution abatement efforts.

6.3 Elasticities of substitution

In this section, we calculate the Allen partial elasticity of substitution (see e.g. Chambers, 1988). It is worth recalling that 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, however, as a results of the all possible interactions among inputs, an increase in one input may be associated to 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. To measure the degree of substitutability between any two inputs, several alternative definitions exist (see, e.g., Stern, 2011, for a critical review about the existing definitions). A widely adopted measure is the Allen partial elasticity of substitution, which is defined by:

$$\sigma_{ij} = \frac{\sum_{t=1i}^{T} x_i f_i}{x_i x_j} \frac{F_{ij}}{F},$$

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.

Fig.3 shows the estimated densities of the Allen elasticities of substitution. Labour and capital, and labour and pollution abatement capital are always substitutes, with median values of the elasticities equal to 1.6554 and 1.6236 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 now negatively skewed, suggesting that capital and pollution abatement capital are substitutes for most firms (the median value of the elasticity is equal to 0.1667) but at the same time they are complements for other firms. Concerning the time patterns of the distributions of these elasticities of substitution,[11] we observe a stability of the annual distributions of elasticities of substitution between labour and capital, and labour and pollution abatement capital. At the opposite, the distributions of substitution elasticities between capital and pollution abatement capital vary over time. The substitutability between these two factors increases constantly over the period, the median varying from -0.1015 in 1993 to 0.3242 in 2007.

6.4 Distributions of efficiency over time

A natural outcome of the estimation of the multiplicative input model is the time-varying efficiency scores. They can be computed as $\exp\left(-\mathrm{E}\left(u_{it} | \varepsilon_{i1}, \ldots, \varepsilon_{iT_i}\right)\right)$ where

[11]Detailed results are available upon request to the authors.

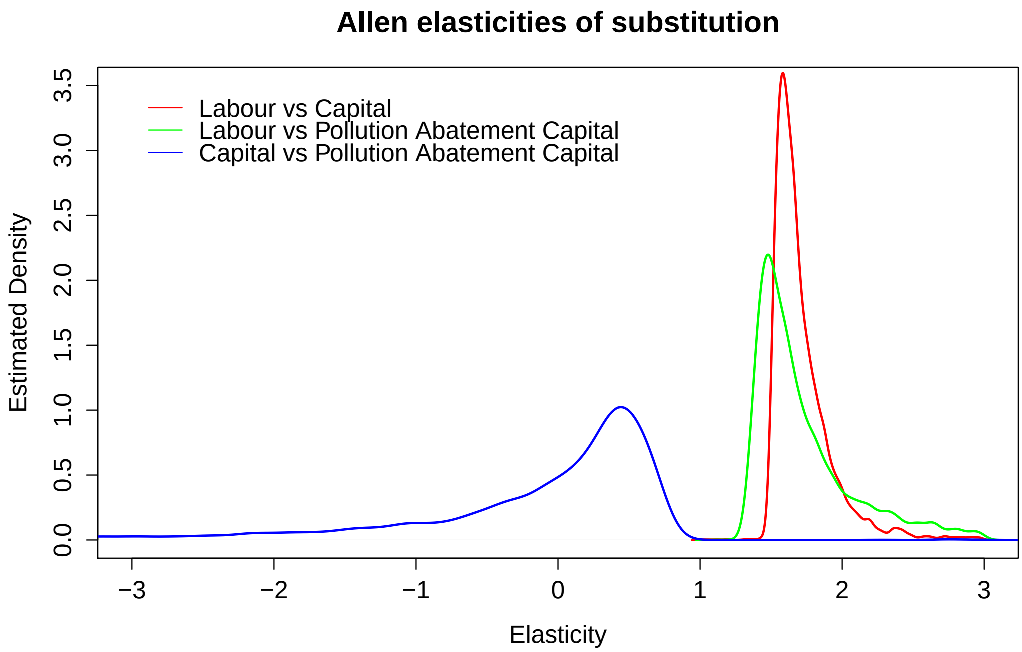

Figure 3: Estimated densities of Allen partial substitution elasticities

$\varepsilon_{it} = v_{it} - u_{it}$, using an extension of the Jondrow *et al.* (1982) estimator of efficiency score to the input model with multiplicative efficiency. Fig.4 reports the annual distributions of these scores. The evolution of these distributions seems to be characterized by different patterns for three periods. The distributions display a slight increase over the 1993-1999 period. The median (resp. mean) of efficiency scores increases from 0.551 (resp. 0.569) in 1993 to 0.580 (resp. 0.604) in 1999, while the dispersion decreases (the standard deviation is equal to 0.234 in 1993 and 0.204 in 1999). This period is followed by a stagnation of efficiency score distributions from 2000 to 2002. Finally, we observe a sharp increase in efficiency scores over the 2003-2007 period. The median (resp. mean) of efficiency scores grows from 0.569 (resp. 0.560) in 2003 to 0.673 (resp. 0.692) in 2007, with a decrease in the dispersion (the standard deviation is equal to 0.210 in 2003 and 0.166 in 1999).

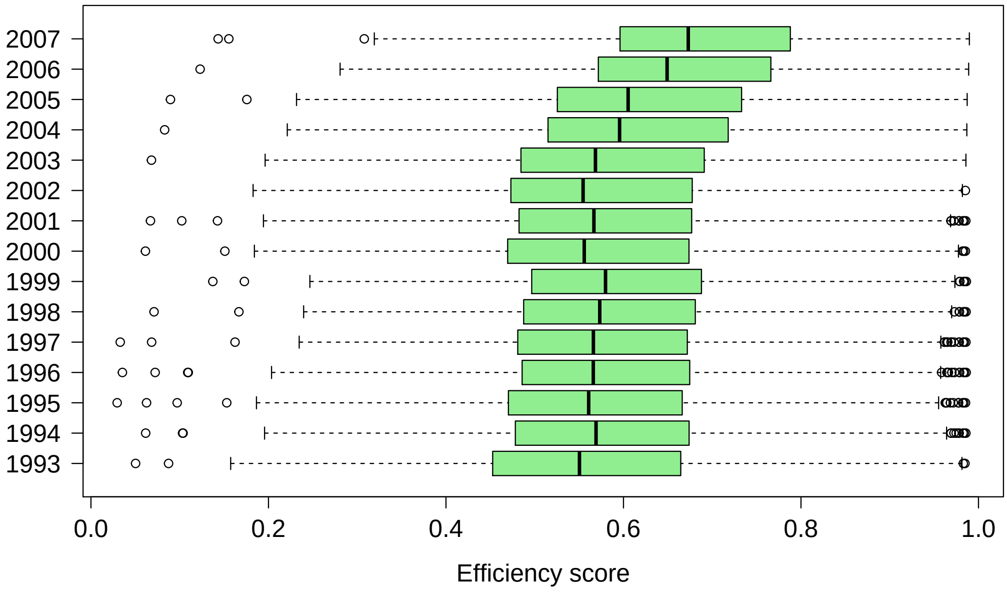

Figure 4: Annual distributions of efficiency scores

6.5 Nonparametric effects on the production frontier and efficiency distribution

This section is devoted to the investigation of the ratios of conditional and unconditional efficiency measures for full and partial frontiers detailed in section 4.[12] Two external factors are considered: year and pollution abatement capital. Fig.5 reports the results of the nonparametric regression of $R_O(x, y|z)$ on z and the nonparametric regression of $R_{O,\alpha}(x, y|z)$ on z using a penalized spline regression approach (Wood, 2006).[13]

The full frontier ratios regression, as reported in Fig.5a, shows the existence of

[12]We calculate conditional DEA estimates with the localizing procedure described in Mastromarco and Simar (2014). Optimal bandwidths have been selected by least squares cross-validation.

[13]Bivariate smooth functions are represented using scale-invariant tensor product smooths (Wood, 2006). The estimation is based on the maximization of a penalized likelihood by penalized iteratively reweighted least squares and it is performed by using the *gam* function of the *R* package *mgcv* (Wood, 2015).

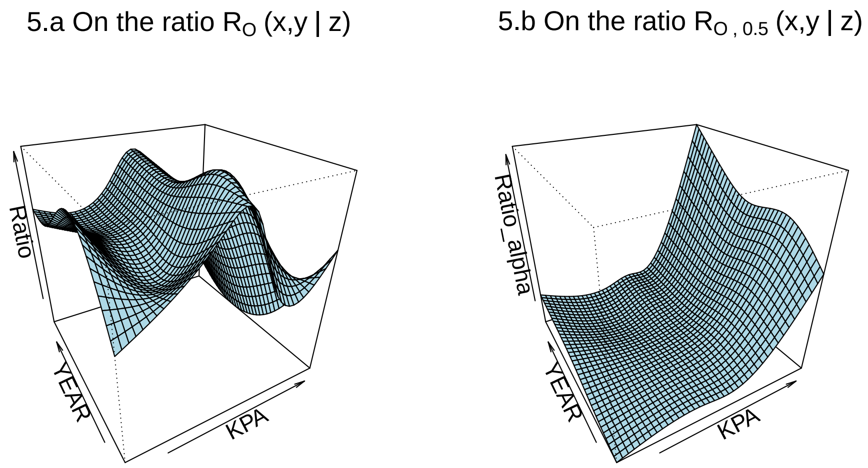

Figure 5: Estimated marginal effects of pollution abatement capital

a nonlinear inverted-U effect of pollution abatement capital on the shape of the frontier, whatever the considered year, indicating a positive effect for low values of pollution abatement capital but a negative one for high levels of such a variable. Then we investigate the effect of pollution abatement capital on the inefficiencies by looking at the ratios of conditional to unconditional order-α quantiles efficiency measures. In particular, by focusing on the median ($\alpha = 0.5$) we observe on Fig.5b a very flat relation for most of the range of pollution abatement capital which becomes increasing for the highest values of such a variable.[14] These results clearly complement the bimodal estimated density of pollution abatement elasticity and the positive but not significant effect of pollution abatement capital on firms' efficiency documented adopting a translog stochastic frontier. On one hand, they appears to be completely consistent with such results. On the other, however, they provide a more thorough picture by i) providing an estimation the functional rela-

[14]In order to check the robustness of our results and to inspect if some extreme observations would hide an effect, we calculate the ratios for partial frontiers with alpha= 0.99, and we obtained very similar results (available upon request).

tion between the shape of the frontier and pollution abatement capital, rather than simply indicating that some firms have a positive elasticity while some others have a negative one, and ii) suggesting a possible nonlinear relation between pollution abatements investments and inefficiencies.

7 Conclusion

This paper revisits the strong version of the Porter hypothesis, i.e. the possible existence of a positive causal relation between well designed environmental regulations and productivity, by exploiting for the first time an original and rich survey on pollution abatement investments conducted on the French food industries. This paper contributes to the existing empirical literature in two main directions. First, taking advantage from recent econometric literatures on productivity and efficiency, we compare the results obtained with two complementary approaches: parametric stochastic frontier analysis and conditional nonparametric frontier analysis. This comparison allows us providing a nuanced and thorough picture of the effect of pollution abatement investments on technology. Secondly, as also stressed by Ambec et al. (2013), the heterogeneity of the effect of well-designed environmental regulations on productivity is a key, but not yet tested, underlying assumption of the Porter hypothesis. Therefore we paid much attention not only on the average effect of pollution abatement investments on productivity - as done in most previous studies - but also focused on its variability across firms and over time. The results from the estimation and testing have relevant policy implications. Indeed, the estimated parametric stochastic frontier, assuming a translog technology, indicates that pollution abatement capital does not influence firms' efficiency but it enters the production function as an input. This seems to be important with respect to a policy oriented perspective indicating that policy makers should consider environmental policies aimed to push firms to invest to reduce pollution not as a mean simply shifting the shape of the production function or the firm's efficiency but as a factor fully affecting the technology of the firms. Secondly, we find that the average elasticity of output with respect to pollution abatement capital is positive and equals 0.018. More interesting, the estimated density of such elasticity appears to be bimodal, with a negative and a positive mode. Moreover, the area under the density for positive values of the elasticity is greater than the same area for negative values, indicating that a large fraction of firms has a positive elasticity while a small part of firms has a negative one. This result appears to be fully consistently with the following statement "Strict environmental regulations do not inevitably hinder competitive advantage against rivals; indeed, they often enhance it" (Porter, 1991, p.168). It also suggests that studying firms heterogeneity may be a key for a better understanding of the Porter hypothesis. Third, we documented a positive shift of both pollution abatement capital elasticity and efficiency over time. The latter being pushed in our model by unobservable common time effects introduced in the model as proposed by Greene (2005). Fourth, pollution abatement capital appeared to be always substitute with labour. It was substitute with capital for most firms; the substitutability between these two factors increased constantly over the period. Finally and very interestingly, the conditional nonparametric stochastic frontier approach complemented the results obtained from the translog specification. Indeed, nevertheless such an approach has been built starting from a very different statistical standpoint, it provides results which are fully consistent with those obtained adopting the parametric model and, at the same time, giving additional insights on the heterogeneity and nonlinearity of the effect of pollution abatement capital on technology. More precisely, these results indicate that for low/average levels of pollution abatement capital, such variable appears to have an "win-win" effect via a positive effect on the shape of the frontier (and no effect on efficiency). For high levels of pollution abatement, instead, such variable has a negative effect on the frontier which is somewhat counterbalanced by a positive one on the efficiency.

In summary, we hope that this paper may stimulate further works. First, it would be of great interest, indeed, understanding if our main results can be generalized to other sectors and countries. Secondly, allowing the effect of pollution abatement investments to interact with other characteristics (e.g. innovative activities) may allow to a better understanding of the complex nonlinear dynamics documented in this paper.

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Additional Materials

Appendix 1 - Vuong test

To define the test, consider two models where $\widehat{f}(y_i, x_i)$ denote the predicted probability of observing y_i and x_i based on the first model, and $\widehat{g}(y_i, x_i)$ the predicted probability for the second model. Vuong (1989) proposes the following test statistics in order to test the null hypothesis that the two models are undistinguishable:

$$V = \frac{M^{-1/2}\ LR_M}{\hat{\omega}_M}$$

where M is the number of observations, LR_M is the usual likelihood-ratio statistics computed as the difference between the log-likelihood of the first model and the log-likelihood of the second model, evaluated at their maximum values, and

$$\hat{\omega}_M^2 = \frac{1}{M}\sum_{m=1}^{M}\left[log\frac{\widehat{f}(y_m, x_m)}{\widehat{g}(y_m, x_m)}\right]^2 - \left[\frac{1}{M}\sum_{m=1}^{M}log\frac{\widehat{f}(y_m, x_m)}{\widehat{g}(y_m, x_m)}\right]^2$$

The Vuong statistics is asymptotically distributed as standard normal distribution. If V is greater than a critical value at a given significance level, say 1.96 for a 5% significance level, then the first model is favored. If V is smaller than a critical value at a given significance level, say -1.96 for a 5% significance level, then the second model is favored. Otherwise, neither model is preferred.

Appendix 2 - Description of the panel

Let us first focus on firm pollution abatement investment behaviour in the panel. The share of firms that have made a pollution abatement investment at least one year during the period 1993-2007, in the 1130 firms constituting the unbalanced panel, is equal to 85.22%. Fig.6 reports the percentages of pollution abatement non investing firms in the different sectors of the French food processing industry.[15] 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 it in the beverage sector.

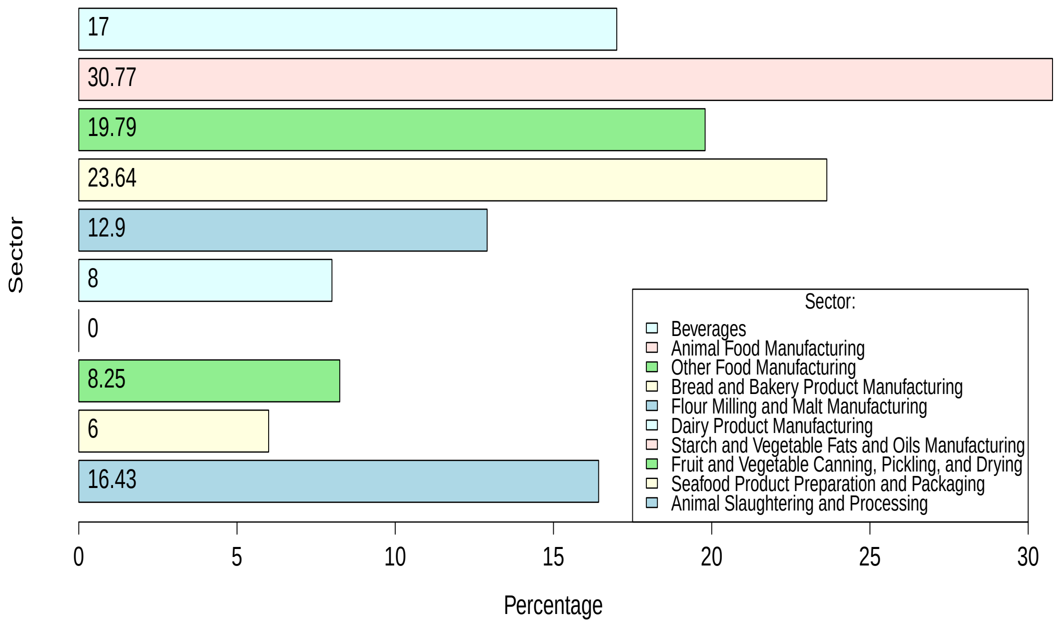

Figure 6: Percentages of pollution abatement non investing firms in food processing industry sectors

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 Fig.7. Such an increase is mostly due to a level shift occurred from 2000 to 2001 when the share of firms investing to reduce pollution moves from 53.06% to 68.82%. This is likely

[15] French food industry can be decomposed in 10 sectors when considering the NACE classification at the 3-digit aggregated level.

due to stricter environmental constraints. In 2000, indeed, the European Union promulgated a relevant directive, i.e., the EU water framework directive, aimed 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 in 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 noticed that the average amount of investments decreases from 320.932 KEuros in 1993 to 247.261 KEuros in 2007 and that such a decrease occurs in the 2000s, as shown in Fig.7.

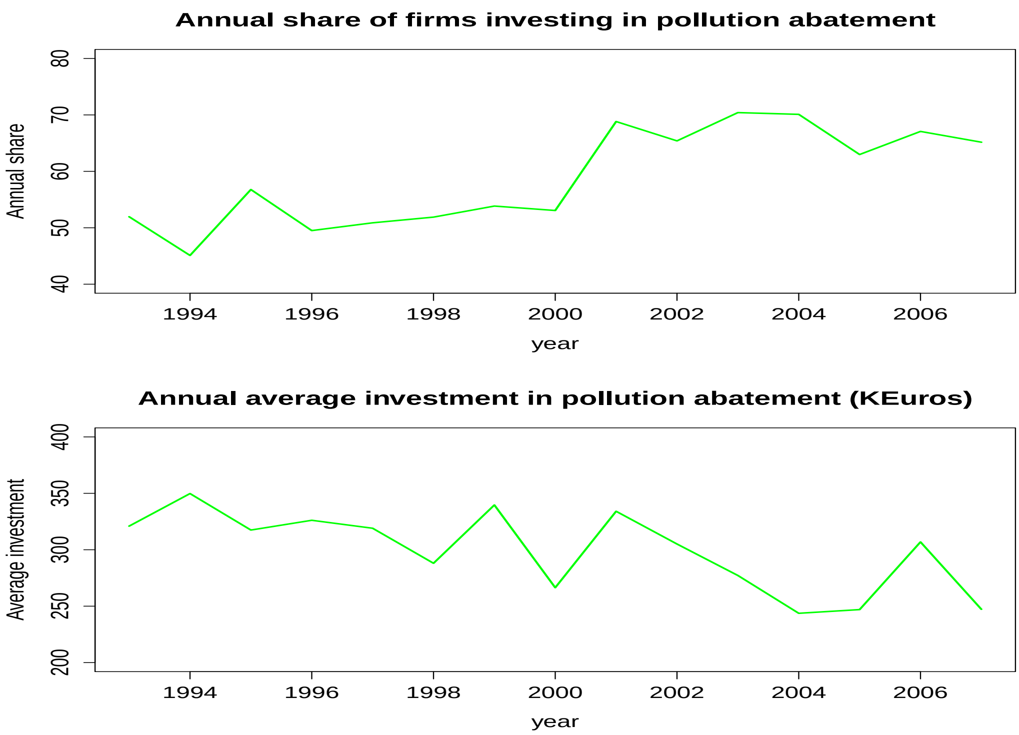

Figure 7: Trends in pollution abatement investments

Fig.8 plots the estimated densities of labour productivity suggesting that firms investing to reduce pollution are more productive than the others and the one sided Kolmogorov-Smirnov test clearly indicates $(p-value < 0.001)$ that the cumulative distribution function of labour productivity for firms engaged in pollution abatements activities lies below that of labour productivity for firms do not engaged in such an activity.

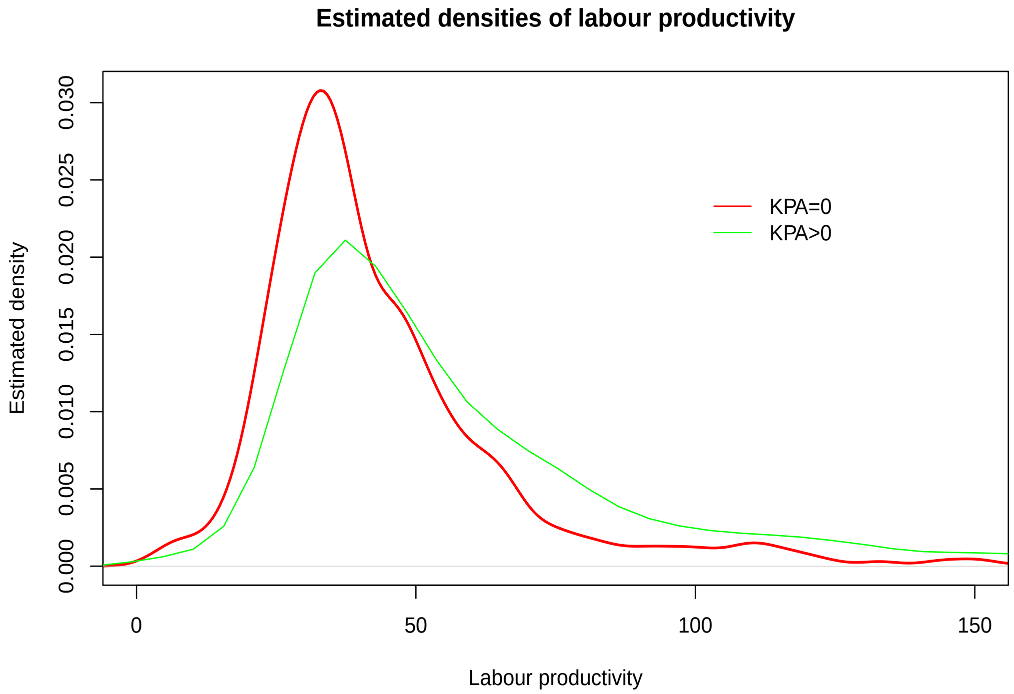

Figure 8: Estimated density of labour productivity