Estimation of stochastic frontier cost function model: An empirical analysis of industrial pollution in Spain

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Abastract:

The purpose of this study is to establish whether the green taxes levied on industrial pollution by certain regional governments in Spain reduce environmental damage through economic agents' responses. Our econometric model reveals that the design of these green taxes produces the desired environmental outcomes, but the impact is lower than expected. Among the possible explanations for this result, we may note that tax rates are too low and are arbitrarily fixed. Also, those green taxes can attain environmental goals but they basically can mitigate financial shortfalls. Finally, and worst of all, agents may react to taxes on industrial pollution by sending it for disposal to other regions that do not apply a charge, or by illegal dumping. These results suggest that the environmental issues related with the production of industrial waste should at least be supervised by central government or coordinated between regions.

Key words: *Environmental policy, GHG taxes, efficiency, stochastic frontier*

JEL Classification codes: H21, H23

1.- Introduction

A key characteristic of advanced societies in recent decades has been the high priority of environmental issues. The environmental impacts and public health issues associated with air pollution management clearly show that this is a scarce resource, the use of which generates evident negative externalities justifying the intervention of the public sector. Externalities are a form of market failure. Because air is "free," it is overused; and thus society suffers from more air pollution than it would if an appropriate price were placed on the consumption of air. In the example of industrial pollution, overconsumption is the result of an imbalance between the industrial's marginal private cost of the clean air (zero) and the marginal social cost. The marginal social cost is the true opportunity cost of the pollution to society. As a separate but related problem, air is a "public good" in the sense that it can be used simultaneously and its consumption cannot be excluded. Where the industry enjoys the benefits of this public good at no extra cost to itself, it will consume away, emitting air pollutants with abandon. This results in an economic problem; the private costs of the industry are not aligned with the social costs of the air pollution, demonstrating the nature of an externality.

Among the possible measures to solve these economic problems, the European Commission has stressed the use of market instruments by the member States to reinforce the effectiveness of their environmental policies, in particular by levying charges on activities that pollute and internalize the negative externality. The European Commission stated in 2001: *The new interest in economic instruments was both reflected in and amplified by the Commission's Task Force Report on the environment and the internal market from 1989, the European Parliament's hearing on economic instruments in June 1990, as well as the decision in Rome by the Environment Council in September 1990 to develop a proposal for a European carbon-energy tax. Both the European Council's Dublin declaration from 1990, as well as the Fifth Environmental Action Programme from 1992 pointed more formally to the need for adopting such new approaches in the use of policy instruments, while the Delors' White Paper on Growth, Competitiveness and Employment signified the wider positive macro-economic implications of such an environmental policy.* As well as serving environmental purposes, such fiscal instruments can be very helpful in budgetary terms at all levels of government, but especially in the sub-central tier, where revenue-raising powers are limited in line with the theoretical recommendations of fiscal federalism.

The specific purpose of this study is to establish whether the green taxes levied on industrial air pollution by certain regional governments in Spain are able to reduce environmental damage through the economic agents' responses. We believe the Spanish experience may throw light on the functioning and effects of environmental taxes on industrial emissions, providing a benchmark against which to assess the potential effects of green taxes in other countries where similar levies are managed by regional governments. Thus, if higher green tax rates do not curtail the generation of industrial contamination, the charge will fail to produce the desired environmental outcomes, even though it may comply with the polluter pays principle.

The study presented here breaks new ground in the field of industrial pollution. We propose the estimation of a costs efficiency frontier using the Stochastic Frontier Analysis (SFA) methodology to provide an individual inefficiency analysis of Spanish industrial plants. Pollution stands for the costs to minimize subjected to a set of control variables, where are included regional emissions taxes. After this brief analysis of frontier framework, the rest of the paper is organized as follows. Section 2 reviews previous literature. Section 3 describes data and methodology and section 4 examines frontier estimation results and the inefficiency effects model, which evaluates the impact of economic variables on individual inefficiency. Finally, Section 5 concludes the paper and presents some political implications.

2.- Industrial pollution: stochastic frontier analysis and previous literature

Analytically, the procedure consists in optimizing a production (costs) function in order to determine the maximum (minimum) value with respect to the given input (output). After that, elements will be ranked regarding their deviation from optimal frontier. Among different methods to estimate inefficiency, it can be selected a non-parametric technique; Data Envelopment Analysis (DEA). The main disadvantage of employing this mathematical technique is that it does not take into account other sources of statistical noise besides the inefficiency (Coelli et al, 2005). Therefore, this method considers that deviations from optimal value are exclusively determined by (production or cost) inefficiency. However, this bias is composed of the failure in economic optimization and random factors, as observed in equation (1). For that reason, we select the parametric technique (SFA)[1].

It is expected to be an adequate analysis tool in the environmental framework, since pollution can be considered as a cost of the industrial plants, caused by output. In this way, frontier pollution will be the minimum level of cost generated as a consequence of the economic activity.

The work of Aigner and Chu (1968) was the original contribution to frontier analysis. That paper attempted to minimize deterministic production functions for cross-section data. Empirical results were highly sensitive to outliers. To overcome this problem, Aigner et al. (1977) and Meeusen and Van den Broeck (1977), independently and simultaneously, suggest frontier estimation with a random and symmetric error term. The model is called stochastic frontier, because output values are subjected to a stochastic element; exp $(X'\beta + v_{it})$.

Many scientific papers have appeared since the seminal contributions of Aigner et al. (1977) and Meeusen and Van den Broeck (1977), proposing diverse reformulations and extensions of the original models, as recently described by Greene (2008) and Belotti et al. (2012). For example, in Schmidt and Lovell (1979) inefficiency is determined by the difference between individual and minimum cost, for a given output assignment. Later, Pitt and Lee (1981), translate this methodology to panel data using the following composed error model:

$$y_{it} = \alpha + x'_{it}\beta + \varepsilon_{it} \tag{1}$$

$$\varepsilon_{it} = v_{it} - u_{it} \tag{2}$$

v_{it} is the white noise and u_{it} is the inefficiency. Schmidt and Sickles (1984) propose three estimation techniques; Generalized Least Squared, Hausman-Taylor and Maximum Likelihood. The last one has a relevant advantage; it is consistent with non-observed heterogeneity, which is necessary to avoid a bias in the estimation.

An important issue in stochastic frontier analysis is the variation of inefficiency over time. Until Kumbhakar (1990), Cornwell et al. (1990) and Batessi and Coelli (1992), literature had considered that inefficiency was constant in the entire sample (Batesse and Coelli, 1988). However, for a large *"t"* panel data, this hypothesis is often

[1]In addition, parametric methods control for heterogeneity among individuals (Farsi y Filippini, 2004).

rejected. For that reason, Cornwell et al, 1990 suggest a model with time-varying inefficiency:

$$u_{it} = w_i + w_{i1}t + w_{i2}t^2 \tag{3}$$

Kumbhakar (1990) proposes a new functional form:

$$u_{it} = g(t) \cdot u_i \tag{4}$$

$$g(t) = \left[1 + \exp(\eta x + \delta t^2)\right]^{-1} \tag{5}$$

Within this framework, if $\eta=\delta=0$, inefficiency does not vary over time. Battese and Coelli (1992) present the notion of *time decay*:

$$g(t) = \exp\left[-\eta(t - T_i)\right] \tag{6}$$

If $\eta < 0$, inefficiency increases over time and viceversa[2]. Finally, Lee and Schmidt (1993) suggest a $g(t)$ composed by time dummy variables.

These investigations assume that time variability is spatially constant. This hypothesis fails when efficiency is affected by environmental factors. Thus, we must tackle the issue of the exogenous variables inclusion in the frontier estimation. These factors have been specified in different ways in applied literature. The procedure has been usually done in two stages. In the first one, inefficiency is estimated without taking into account these exogenous factors, and another in which, the regression is estimated based on these factors. A key contribution was made by Batessi and Coelli (1995), who formulated a one-step efficient calculation procedure for a dynamic panel data, which overcomes certain inconsistencies in earlier models. These techniques can be translated to a pollution frontier model, capturing the behavior of industrial plants, which would consist of a regression model with two error terms, $"v"$ and $"u"$, as follows:

$$y_{it} = \alpha + x'_{it}\beta + v_{it} - u_{it} \tag{7}$$

In this model, the dependent variable is the industrial plant´s pollution. As observed, the error component must be decomposed into random factor and inefficiency. We assume that:

$v_j \sim N(0, \sigma^2_v)$.

[2] In the last period t=T, then, inefficiency is in base-level. If η>0, inefficiency decreases.

$u_{jt} \sim N(0, \sigma^2_u)$.

"u_{jt}" must be distributed as a truncated normal with mean of zero (half normal), that only takes positive values (Caudill et al, 1995), because its observations are always above frontier. The interpretation of error term *"u_{jt}"* in a cost frontier model is different with respect to that we have to do in present framework. In our case, inefficiency must be considered as the potential abatement of pollution non-achieved.

In this point, we will also estimate an efficiency effects model in order to capture the impact of exogenous factors in efficiency distribution, attending to Battese and Coelli (1995).

$$u_{jt} = \delta' z_{jt} + \varepsilon_{jt} \quad \text{where} \quad u_{jt} \geq 0 \tag{8}$$

$\delta' z_{jt}$ is the vector of exogenous variables for specific characteristics. Then, Bastesse and Coelli (1995) permit the one-step dynamic frontier estimation. However, if there are unvarying non-observed factors that affect the optimization, model will not be adequately specified. Thus, Greene (2005a; 2005b) proposes a new model, in which, the intercept is individually estimated. The general specification (1) is modified as follows:

$$y_{it} = \alpha_i + x'_{it}\beta + \varepsilon_{it} \tag{9}$$

Anyway, Greene (2005b) also pointed that any model is not completely satisfying. For that reason, we implement both specifications under two different scenarios. Once reviewed the methods to estimate frontier, we can determine the degree of industrial plant´s cost efficiency. Analytically, it is the rate between individual cost and the minimum cost (frontier value):

$$CE = C_{jt}/C^F_{jt} \tag{10}$$

Cost efficiency takes values in the interval (0, 1). It represents the emissions of each industrial plant with respect to the optimal level of pollution, determined by the frontier. If environmental inefficiency does not exist, *"$ui=0$"* and *"$CE=1$"*, that is, the industrial plant achieve the minimum level of pollution for a given set of exogenous factors. In case of CE<1, the industrial plant could abate its pollution regarding frontier value.

The error term *"u_i"* is not observable, however, it must be inferred from *"$\varepsilon_i = v_i - u_i$"*, thus, the individual cost efficiency can be calculated through the method proposed by Battese and Coelli (1988), as follows:

$$EF_i = E[\exp(-u_i) | \varepsilon_i] \quad (11)$$

Due to the scarcity of literature on the application of stochastic frontier to pollution, we have taken into account different works related with farm efficiency. Battese and Coelli (1995) is also one of the most relevant contributions, from an empirical point of view. They estimate the production efficiency for a set of Indian farms. That paper includes a Maximum Likelihood Estimation (MLE), where the output is the dependent variable, and land, labor, time variable and the number of bullocks are the independents. They also implement an inefficiency effects model, where dependent variable (inefficiency) is related with a set of control factors (age, schooling and time variable). They test whether inefficiency effects are not stochastic, which, is rejected by regarding for evidence. Before that, Tihansky (1973) had exposed a general theoretical model to maximize the profits of regional firms subject to constraints of environmental quality and resource scarcity for production.

In Spain, Puig-Junoy and Argilés (2004) use a translog production function for a panel of Catalonian farms. In line with prior literature, the output farm is determined by the following inputs: overhead and specific costs, fixed capital, current assets and work units. The inefficiency model includes different variables like age of farmer or accounting use, among others. Their empirical evidence estimates an average efficiency of 62.3%.

Coelli et al. (1999) apply stochastic frontier for a sample of international airlines with the aim of analyzing the environmental efficiency. In the frontier model, the independent variable is represented by output, subjected to labor, capital and a deterministic trend. On its hand, inefficiency is related with aircraft characteristics and local factors. It is proved the existence of a significant superiority in Asia /Oceania with respect to Europe/North America, attributed to environmental factors. Efficiency in distribution of electric energy has been frequently investigated. Hattori (2002) compares efficiency in electricity distribution between Japan and United States. This paper concludes that Japanese system is more efficient. Finally, in reference of environmental efficiency, Perkins and Neumayer (2008) prove two hypotheses; the first one states that dirtier economies improve efficiency faster than cleaner ones, since they adopt new technologies. Second, they claim that “transnational linkages accelerate the improvements in environment efficiency”.

Once reviewed prior literature, it is noted that applying stochastic frontier in the study of the GHG emissions is an innovating technique in environmental literature and allows broadening research field.

3.- Data and methodology

In this section, we estimate the stochastic cost frontier for a set of industrial plants in Spain. Cobb-Douglas and translog are the procedures to perform the Stochastic Frontier Analysis. Among them, we have selected the translog function, because it is a more flexible specification. The cost frontier is expressed as follows:

$$C_{it} = C(y_{it}, p_{it}, x_{it})\exp(\varepsilon_{it}) \tag{12}$$

Where:

- C : cost
- y : output
- p : price
- x : input

Applying natural logarithms on both equation sides in (12):

$$\ln C_{it} = \ln(y_{it}) + \ln(p_{it}) + 1/2*\ln(p_{it}^2) + \Sigma\ln(x_{it}) + v_{jt} + u_{jt} \tag{13}$$

In a similar line of research, we can observe the paper of Puig-Junoy and Pinilla (2008) that estimate a translog stochastic-frontier production function to examine the causes of the regional differences in technical efficiency among Spanish regions. Dependent variable is composed of three gases: CO_2, NO_X and SO_X for 146 industrial plants over period 2001-2011 (EMISSIONS). *Sample* is collected taking into account the emissions that exceed the threshold established in Spanish Royal Decree RD 508/2007 and are available on the web page of the *Spanish Register of Emissions and Pollutant Sources (PRTR-España)*[3]. The environmental damage is standardized as determined by European Commission Decision 2000/479/CE:

1 Pollutant Unit CO2 = 100000 Tons CO2;

1 Pollutant Unit NOX = 100 Tons NOX;

[3] It provides information to the public on the pollutant releases to air, water and land, and off-site transfers of wastes not only from the main industrial facilities but also releases from other point and diffuse sources, according to the international (Kiev Protocol and Aarhus Convention), European (E-PRTR Regulation) and Spanish regulation (*Real Decreto 508/2007* and its amendments).

1 Pollutant Unit SOX = 150 Tons SOX

Sample has been selected intending to reflect the weights of the following sectors thermal generation (34%), cement manufacture (26%), chemical industry (12%), oil refinery (6%) and others (22%). With respect to independent factors, we have selected a set of variables that may affect the determination of the frontier, since they are expected to be related with industrial emissions.

Firstly, we suggest the employ of a tax variable, as a proxy of the price, calculated as the quotient between the tax rate and the individual pollution (TAX). That helps us to measure the impact of the regional taxes on private behavior. If fiscal policy is able to provide a strong incentive, the optimal pollution will be negatively affected for taxes. In the sample, the 35% of plants have to pay an emission tax (those located in regions where tax is approved), and the rest of them are not subjected[4]. This fact can reduce its environmental effectiveness, since pollution cost varies geographically and the incentive is weaker. Our model is an interesting tool to prove this hypothesis. In other line, and with the purpose of testing the existence of a quadratic form among regional taxes and pollution, our model subsumes the following factor ($1/2*TAX^2$).

The mother company operating income (OPEINC) is a proxy of the output, and its sign is expected to be positive. According to the scale effect, as long as pollution is a normal input, an increase in production will raise the need of pollute. The input (PERM) is intended to represent the impact of the emissions trading system in the optimization. This cap-and-trade instrument, denominated, European Union Emissions Trading System (EU-ETS) has been implemented in 2005-2007 and 2008-2012[5], regarding historical pollution. The main purpose of this system is to meet the need of private emissions and control for the final volume of pollution, for that reason, we expect a positive correlation between allowances and emissions[6].

Our functional form also includes two quantitative variables associated with technology. The age of the company (OLD), which represents the exogenous technology, as suggested by Cole, Elliott and Wu (2008); and material asset (MA), as a proxy of the investment in technology. Their sign is supposed to be negative, since

[4] GHG taxation in Spain is limited to the regional level of government, where only five regions have introduced a tax on air pollution (*Andalusia, Aragon, Castile La-Mancha, Galicia and Murcia*).

[5] Implementing these plans of assignment has been developed by national governments. After first January 2013, allocation is a responsibility of European Union.

[6] Emissions above cap are tax- exempted in order to avoid duplicate payment.

under the technology effect principle, this variable is crucial to mitigate pollution through innovation. Finally, input expenditures (INP) are included to test whether relationship between pollution (considered as an input) and the remainder of inputs is complementary or substitutive. The functional form is represented as follows:

$$\ln(\text{EMISSIONS})_{jt}=\beta_0+\beta_1\ln(\text{TAX})_{jt}+½*\beta_2\ln(\text{TAX}^2)_{jt}+\beta_3\ln(\text{OPEINC})_{jt}+\beta_4\ln(\text{PERM})_{jt}+\beta_5\ln(\text{MA})+\beta_6\text{lN}(\text{AGE})+\beta_7\ln(\text{INP})+v_{jt}+u_{jt} \quad (14)$$

On the other hand, the inefficiency effects model will be estimated taking into consideration a set of dummy variables and a quantitative variable (INTER). The latter is intended to analyze the impact of the interaction among policies (taxes and allowances) on efficiency. This factor allows us to compare the emissions rights effect, if an industrial plant is subjected to the pollution tax. We forecast a positive sign since under hypothesis that rights will be more effective if taxes are jointly implemented.

With respect to qualitative variable, the first one, denominated (DBDT), is the result of the interaction between DB and DT, both suggested by Lin and Li (2011). DB is a dichotomous variable, which takes a value of 1 if the industrial plant is subjected to the emissions tax, *and zero otherwise*. On the other hand, DT takes 1 for the period 2006-2010, when all regional emissions taxes were already implemented, *and zero otherwise*. For that reason, interaction allows analyzing the existence of spatial differences in industrial pollution, and it sign is supposed to be negative.

We also examine the sectoral impact on inefficiency through four dummy variables that take the value 1, if the observation belongs to an industrial thermal power plant (THE), an oil refinery (REF), a chemical industry plant (CHE) or a cement manufacture plant (CEM). Our model is:

$$u_{jt}= \delta_1\text{DBDT} + \delta_2\text{INTER}+ \delta_3\text{THE} + \delta_4\text{REF} + \delta_5\text{CHE}+ \delta_6\text{CEM} + \varepsilon_{jt} \quad (15)$$

After estimation, we let expose a graphical analysis to reinforce our econometric evidence conclusions. In summary, independent variables are presented in table 1:

Table 1: Independent variables

Variable	Definition	Source	Exp. Sign
Frontier			
OPEINC	Operating income (output)	Iberian Balance Analysis System	+
PERM	Permits EU-ETS (input)	Ministry of Agriculture	+
TAX	((Tax rate)/ Emissions)	Regional legislation	-
½*TAX^2	½*((Tax rate)/ Emissions)^2	Regional legislation	-/+
MA	Material Asset	Iberian Balance Analysis System	-
AGE	Age of the company	Iberian Balance Analysis System	-
INP	Input expenditures	Iberian Balance Analysis System	+/-
Inefficiency			
DBDT	Tax	-	-
INTER	Interaction among taxes and allowances	Ministry of Agriculture/ Regional legislation	+
CEM	Cement manufacture	Spanish Emissions Register	+
THE	Thermal generation	Spanish Emissions Register	+
CHE	Chemical industry	Spanish Emissions Register	+
REF	Oil refinery	Spanish Emissions Register	+

4.- Results obtained from the industrial pollution frontier and inefficiency

We perform two different estimations of the stochastic frontier model. On one hand, we have implemented the model proposed by Batessi and Coelli (1995), whereby industrial plants share the constant term of the specification; and, alternatively, we have carried out Greene (2005b), in which the intercept is different for each industrial plant. We display results in table 2.

Both estimations consider that the inefficiency may vary over time and exclude the non-observed and time-invariant heterogeneity from inefficient term. The left-side column of table 2 shows the estimation results of model proposed by Batessi and Coelli (1995), under the name BC95. In the second column, we can see the model Greene (2005b), denominated G05.

To verify the adequacy of stochastic frontier estimation methodology, we contrast the following null hypothesis (Ho: $\gamma = \sigma^2_u / (\sigma^2_u + \sigma^2_v) = \sigma_u^2/\sigma_\varepsilon^2 = 0$), which quantifies whether the contribution of the variance of u to the total variance in the error term ε is significant. Since estimator "λ" is significant in both models, and "γ" take a value closed to one, the error component variance (due to inefficiency) is relevant, and the null hypothesis is consequently rejected. On the contrary, if $"\gamma = \sigma^2_u / (\sigma^2_u + \sigma^2_v) = 0"$, all deviations are white noise. $"\sigma^2_u"$ is null and $"u"$ must be removed from estimation.

The tax variable (TAX) is only significant in Greene, 2005, and it is positively related with industrial pollution in both cases (in the optimizing process), as well as, ½*(TAX^2), it is interesting to analyze briefly what is behind this result. Firstly, Spanish regions have lower levies than the northern European countries (see OECD database) and consequently, companies are no encouraged to abate pollution, maintaining optimal frontier too high. Moreover, the number of taxpayers is also very low, which reflects that the environmental goal is overcome by the need to reduce public shortfall. Likewise, most emissions taxes have been recently implemented, so its low effectiveness may be influenced by this fact.

The variable related to business economic activity (OPEINC) only affects to pollution in G05 estimation. In fact, the positive and significant effect would indicate that the income evolution of companies increases their polluting behaviour. This is consequence of the scale effect that indicates what happens to the demand for the firms' inputs (in this case, pollution can be considered as an input required for output), as the firm expands production.

The emissions trading system (PERM) influences positively the pollution, which is consistent with the theoretical hypothesis. However, it may be surprising that the positive sign of a mechanism of externalities correction determines their effectiveness. This is due to the purpose of the system, which is the mitigation of global emissions, by establishing an overall limit (cap) on pollution. Thus, the volume allocated to each plant, should be similar to the volume finally emitted. Therefore, the mechanism of mitigation is the market price faced by companies, if they want to pollute beyond the assigned level.

With respect to technological variables included in our model, the first one captures the relative weight of the exogenous technology (OLD) and it is negatively significant in G05 model, while investment in fixed assets (MA) reveals the same result. This relationship is nothing more than a reflection of the ability of technology to mitigate pollution and encourage innovation, in line with the institutional reports (Environmental Protection Agency, OECD, European Union…) and academic researches, like Picazo-Tadeo and García-Reche (2005). This latter analyzes firms' environmental performance measured as the ability to reduce polluting wastes for a level of output, through DEA technique for a sample of ceramic-tile producers in Spain. They find that technological innovation promotion improves firms' environmental efficiency.

As cited above, one of our goals is to examine the type of existing relationship between pollution and the remainder of inputs. For that reason, we have included (INP), and depending on its sign, we let conclude about the complementarity or substitutability of this relation. Our result in G05 model stresses that an increase in the remainder of inputs supposes a raise in pollution, thus, relationship is complementary. This fact can be related with the scale effect, mentioned above, since it states that an improvement of business activity will entail an increase in inputs (included in variable INP), and also, in pollution (given the significativity of OPEINC), and consequently, among them.

Finally, for the variables specified in explaining the inefficiency, we may note that most sectors (cement manufacture, oil refinery and chemical industry) do not have an impact on inefficiency in both models. However, the case of thermal generation represents an exception, in so much as, it is significant at 1%. That denotes that thermal generation is a highly pollutant process, and the efficiency associated with thermal plants is considerably lower than the rest of sample. For that, we have to stress the importance of the type of productive process in the environmental mitigating policy. With respect to interaction variable, its coefficient is negatively and significantly related with inefficiency, so, we may note that the efficiency's average associated to industrial plants which are affected by both policies is higher.

On the other hand, the variable related with the GHG tax has a great influence on efficiency, in G05 model. Then, the estimated effect proves the existence of the tax impact when struggling efficiency improvements. These results match theoretical expectations and are in line with the available empirical evidence (Larsen and Nesbakken, 1996; Bosquet, 2000; Andersen et al. 2001; Bruvoll and Larsen, 2004; Patuelli et al. 2005).

Nevertheless, this result is likely to be contradictory to that obtained in frontier estimation, where taxes increase optimal pollution. However, in this case, the coefficient only reflects that companies, which are subjected to the tax, improve efficiency more than others, but this increase is weaker than expected, as levies are very low. In order to throw light on the inefficiency's analysis, we provide a detailed study of the differences in this variable, across groups of industrial plants.

Table 2: Stochastic frontier and inefficiency effects model

Frontier	**Batessi and Coelli, 1995 BC95**	**Greene, 2005b G05**
ln(TAX)	0.0451031 1.01	0.1683364*** (7.52)
½*ln(TAX)	0.0042616 0.85	0.0162692*** (6.80)
ln(OPEINC)	-0.0128961 -0.17	0.0747939* (1.90)
ln(PERM)	0.8313732*** 7.56	0.458268*** (8.38)
ln(MA)	-0.0224755 -0.34	-0.2099454*** (-5.03)
ln(AGE)	0.0701919 1.03	-0.1829744*** (-3.38)
ln(INP)	0.0508546 0.61	0.2159919*** (4.69)
Cons	-9.681374*** (-6.58)	-5.770984*** (-6.99)
λ (Ho: γ =0)	1.820156*** (7.66)	3.123214*** (47.32)
σ_u^2	1.123786*** (5.06)	0.8067485*** (15.09)
σ_v^2	0.6174118*** (11.35)	0.2583071*** (10.05)
$\gamma = \sigma_u^2/\sigma_\varepsilon^2$	0,64540	0,75747
Inefficiency		
INTER	0.000606 (0.36)	-0.0014401** (-2.43)
DBDT	-1.009322 (-1.33)	-1.415098*** (-4.59)
CEM	-1.449058 (-0.90)	-1.929844*** (-4.10)
THE	1.456004*** (4.21)	1.485694*** (7.79)
CHE	1.11943** (2.45)	0.2655816 (0.76)
REF	0.9367782 (1.21)	-1.819162** (-2.08)
Cost efficiency		
Mean (TAX / Non-TAX)	(0.52193 /0.439448)	(0.722799/0.473174)
St. Dv. (TAX / Non-TAX)	(0.2045643/0.220486)	(0.186989/0.27958)
Min. (TAX / Non-TAX)	(0.058152/0.0134831)	(0.033197/.0127006)
Max. (TAX / Non-TAX)	(0.876721/0.833360)	(0.95138 /0.939408)

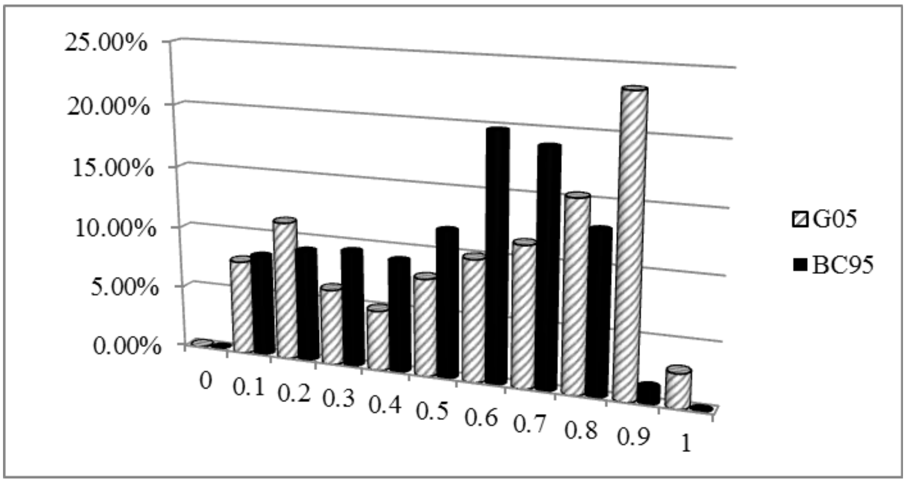
Significantly different from 0 with a confidence level of 90 (*), 95 (**) and 99 (***) percent in a two-tailed test.

Once given the suitability of using the stochastic frontier methodology to study the industrial emission *reduction potential*, the last step is the calculation of the efficiency (mitigation effort) in each industrial plant. Jondrow et al. (1982) suggest the following equation:

$$\text{Efficiency} = \exp[-E(-u)|e] = \exp(-\hat{u}_{it}) \quad (14)$$

This calculation for G05 model shows that, under the stochastic frontier methodology for panel data, there is no plant that makes use of its potential at 100%, although in Figure 1, we can see that many plants (at least 30%) are close to its border, as they perform an effort above 80%. Meanwhile, for BC95 model, the efficiency is concentrated around 60%-70%. Thus, the distribution of the inefficiency varies depending on the estimating technique (BC95 or G95), but the resulting sectoral ranking hardly varies (excluding oil refinery, see Table 3), which reinforces the consistency of the results obtained.

Figure 1: Efficiency distribution



Source: *own elaboration.*

If we compare average data, Table 3 shows that the degree of mitigation effort in the sample is between 46 and 55%, depending on the estimated model (BC95 or G95). The average degree of efficiency in cement manufacture increases between 17 and 22 percentage points in both models (with respect to entire sample), ranging between 63% and 77%. This is understandable, given the high degree of technological innovation in this sector, reflected in the negative significativity of the parameter in the model G05. With regard to thermal plants, it seems that the efficiency in this sector stands at 33%

with the BC95 model, and 31% with G05. Most of plants that occupy the bottom of the distribution belong to this sector. So, we can clearly conclude that it is the less efficient sector in line with econometric evidence (Table 2). Among possible explanations for this result, it is worth taking into consideration the type of productive process. Therefore, we suggest a set of public interventions (new coal regulations …) to strengthen the environmental goals in this sector.

The chemical plants efficiency level is lower than sample average as reflected in the estimated parameter of BC95 (see table 2), and the efficiency associated to oil refinery plants is concentrated in a score of 79% for G05 and in 36%, for BC95. To understand this contradictory result, we may note that there are *too few observations* for this sector, and it can lead to inconsistent results.

Table 3: summarize statistics by sector of activity

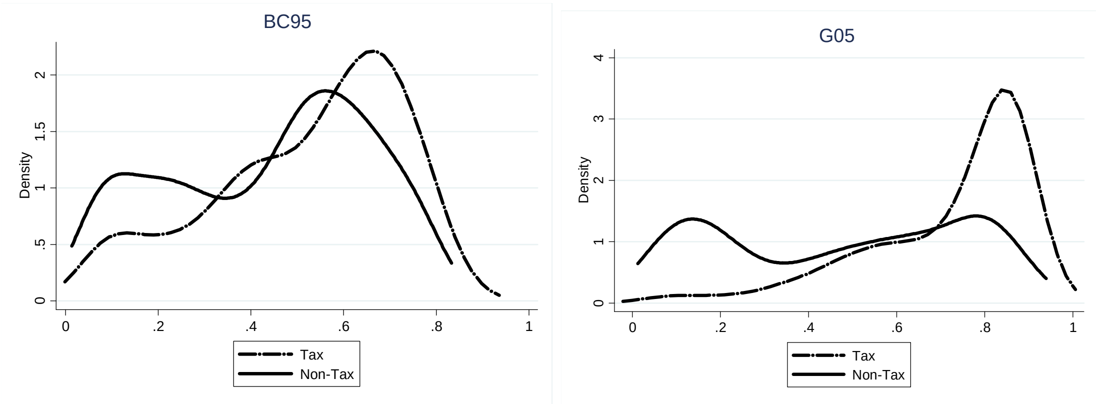
	Environmental effort			
	Mean	**Std. Dev.**	**Min.**	**Max.**
Total sample				
BC95	0.4660885	0.2187862	0.0134831	0.8767216
G05	0.5537914	0.2789221	0.0127006	0.9513823
Cement manufacture				
BC95	0.6350079	0.1061086	0.2749266	0.8767216
G05	0.7740257	0.1204129	0.1765632	0.9419658
Thermal generation				
BC95	0.3311822	0.2166151	0.0134831	0.8333608
G05	0.3134939	0.2425758	0.0127006	0.9174087
Chemical industry				
BC95	0.3254845	0.1553268	0.0857208	0.6900353
G05	0.4755862	0.2154297	0.147216	0.8938816
Oil refinery				
BC95	0.3694215	0.1318279	0.1623013	0.6781799
G05	0.7950225	0.125895	0.2425018	0.9394083

Source: *own elaboration.*

Finally, in order to draw an accurate conclusion about tax effectiveness, and improve the previous models, we present a graphical analysis of efficiency densities for two subsamples (Figure 2). The first one is composed of plants that pay the GHG tax, and the other one, the rest of sample. The main conclusion is that the difference between them is hardly significant in BC95. As expected, the efficiency of companies that pay emissions tax (around 70%) is slightly higher than others (60%). Nevertheless, in reference to G05 model, we can observe a great difference inter-groups in line with econometric evidence (see table 2). This latter reflects that more than 30% of companies are above 80% of efficiency. We use a Kernel density function, let K be the density, and h the bandwidth:

$$f(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \tag{15}$$

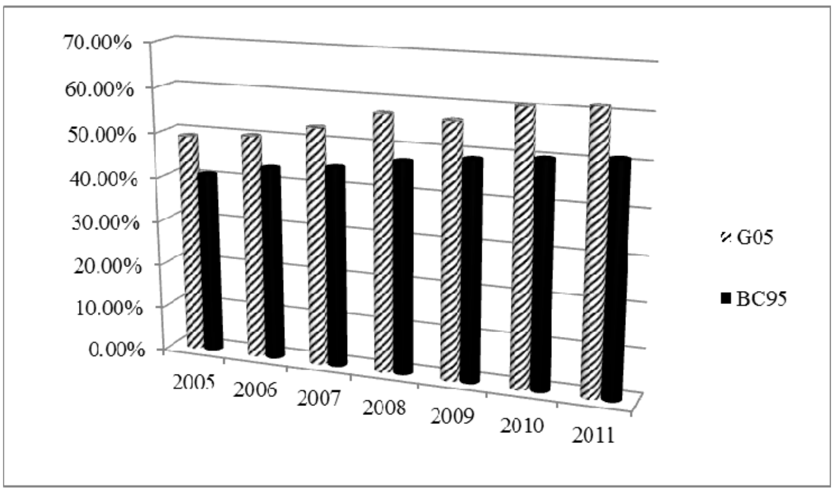
Figure 2(a, b): Comparison among efficiency's densities



Source: *own elaboration.*

On the other hand, if the evolution of efficiency in the period under study is analyzed, it is worth mentioning that it varies weakly, as shown in Figure 3. Despite the significant differences between models, the results suggest that there is scope to improve efficiency in both cases, which is higher in BC95 (50%) than in G05 (40%).

Figure 3: Efficiency over time



Source: *own elaboration.*

5.- Conclusions and political implications

The continued growth in global air pollution has led to an increase in environmental awareness that has raised concerns over the potential consequences of climate change. In this context, the role of industrial plants is critical, as they represent an important part of total emissions (approx. 70%). In this investigation, we have intended analyzing the scope for improvement in the environmental efficiency for a set of Spanish industrial plants. To face this objective, we have calculated the average mitigation effort as the rate between individual and potential pollution, the latter estimated by the technique of stochastic frontier. This method is justified, because the estimation of an OLS function to capture the industry's behavior is inconsistent. Our empirical results indicate that deviations from pollution frontier are due to not only the estimation error, but also to inefficiency.

The implementation of this technique makes our work one of the first empirical contributions in this methodology, intended to calculate the potential of emissions abatement through stochastic frontier. The main empirical conclusions can be summarized as follows. Our models reveal the existence of a very important change in inefficiency due to the tax, but it is positively related with pollution when optimized. This could derive from the fact that tax rates are hardly able to create an appropriate incentive to reduce pollution and improve the cost efficiency. Graphical results support this hypothesis, as we can see in Figure 2. This empirical evidence has been tested through two common methods of frontier analysis: Battese and Coelli (1995) and Greene (2005b). On the other hand, the European Union-Emissions Trading System has a relevant shock on frontier estimation, according to our empirical results. Therefore, it seems to influence on industrial pollution and reflects the need of an international control policy. In this way, taxes will generate a shock on allocated emissions, and once overcome the limit; the market price will be the mitigating instrument. The political effectiveness will depend on the environmental effort implemented to this end.

The calculation of the mitigation effort for industrial plants allows us to draw various conclusions. In general, there is a large room for improvement of environmental efficiency, but this purpose requires an intervention in two fields. First, private firms have to promote research and technological innovation, and secondly, public sector must implement an effective fiscal policy, since empirical evidence shows that regional taxes have hardly achieved a positive impact in environment. Consequently, the required green-oriented tax reform has to be well-designed to encourage a change in private behavior. Furthermore, from a sectoral point of view, we may stress the case of thermal power generation, highly polluting and whose efficiency is very low, according to both estimates. This can be solved with different policies based on stricter regulations of sector activity and greater control over its production. On the other side, industrial plants associated with cement manufacture has shown a more efficient behavior than sample average.

Finally, it is worth stressing that due to the challenge that climate change represents for global stability, we suggest to legislators include a set of harmonized and coercive instruments. Specially, our proposal contains the implementation of a better fiscal policy, which entails a stronger incentive to private agents, and its coordination with the allocation system. In addition, sectors like thermal generation require a specific regulation to ensure a more efficient behavior.

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