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Environmental Variables and Power Firms' Productivity: Micro Panel Estimation with Time-Invariant Variables.

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Abstract

Internal and external institutions play a crucial role in the firms' decision-making process and their productivity. Along with internal institutional features, such as the corporate ownership structure, external institutions, such as the stringency of market and environmental regulations, shape the framework in which firms operate. This research explores the role of these determinants and their interactions in affecting the productivity changes of the power generating firms in 15 European countries between 2010 and 2016. In a first step, using the firm-level ORBIS dataset, we first the productivity changes over time of power generating companies (NACE Code Rev.2.3511) using the global Malmquist index. Then, in a second step, dynamic panel linear model is applied to investigate how the internal and external institutional variables affect the dynamic of the global Malmquist index. In a preliminary analysis a wide range of tests are performed to detect the presence of outliers, the returns to scale, the correlation among inputs, outputs and the productivity indexes, the independence between the distribution of the productivity indexes and the second-stage institutional variables. The institutional variables are almost time-invariant, the procedure proposed by Kripfganz and Schwarz (2019) is applied to consistently identify the effects of time invariant variables. This new method provides valuable robustness against wrong assumptions on the exogeneity on the instruments. To capture the interplay among external and internal institutional variables, interaction variables are used. Results highlight the need to fine-tune the environmental regulation with the firm-specific internal features, to avoid hindering firm-level productivity in the power generation sector.

Keywords: Environmental and Market regulation, Time-Invariant Variables, Global Malmquist Index, Electricity Sector

JEL Classification: C2 L5 L9 O4 Q4

1 Introduction

This research analyses the dynamic of productivity of the European power sector computing the global Malmquist Index of a large set of power generating utilities between 2010-2016. Comparative statistic analysis may lead to bias interpretation if the computed productivity indexes are not explained considering the macroeconomic context and the market conditions. Firms' productivity is indeed influenced by discretionary and non-discretionary factors, and only the former are under managers' control. Non-discretionary variables mainly refer to the institutional environment in which firms operate. Therefore, researchers have to properly control for exogenous environmental variables and other non-discretionary managerial factors that, at the time of the production planning, can affects the patterns of efficiency indexes. The institutional environment is defined by external and internal variables. The main external features are the stringency of the market and environmental regulations, that define the different incentive mechanisms and compliance strategies affecting firms' performance; the internal firm-specific variables refer instead to the ownership structure (if the firm is a state-owned or private utility and the degree of ownership concentration) that may explain the different firm's objective functions, that could be more complex than the simple profit.

The research has three specific objectives: (i) to identify potential differences in the performance of Europe-based electricity companies according on the institutional environment in which firms operate; (ii) to analyse the role of the interplay between environmental regulation and the corporate ownership specific variables on explaining these dissimilarities; (iii) to propose a novel technique based on two stage Generalized Method of Moment (GMM) that allows the robust identification of the effects of the time-invariant institutional variables.

We start computing the output-oriented global Malmquist Index (MI) to describe the performance of power generating firms from 2010 to 2016. The effects of non-discretionary variables on MI are then estimated using dynamic panel linear models. A preliminary analysis is also performed to ensure rigorous results; this analysis has involved a large set of tests concerning the potential endogeneity of inputs, the detection of outliers, the returns to scale and the separability condition that validates the second stage GMM procedure.

The European electricity reform process has introduced privatization and liberalization, giving rise to a mixed oligopoly framework, with private and public ownership coexisting in many countries. More recently, environmental regulation has acted either as a constraint or opportunity for the development of the electricity sector, affecting the product market competition and performance (Knittel et al. 2019; Wang et al. 2018). Therefore, analysis of performance must enlarge the framework accounting for the interaction between corporate framework and environmental policy, whose effects on the firm-level processes can be different, according to the ownership structure.

Most studies that investigate the impact of regulation on the productivity of the electricity sector focus on one type of policy or one instrument without considering the coexisting effects of different kinds of policies. In this paper, both market and environmental regulations are analysed and their separate and join effect on the firms' structure are considered to address the current policy debate.To our knowledge, this study is the first attempt to provide a comprehensive scheme of the different institutional variables conditioning the performance of power generation firms after the global financial crisis of 2007–2009. Literature has provided rather weak evidence; practical problems concern the limited temporal and cross-sectional dimensions of the data and the applied estimation strategies (Kozluk and Zipperer 2015). Our sample encompasses instead 655 power generating firms spread across 15 European countries, therefore, it is sufficient large in terms of cross-sectional dimension. The cross-country dimension makes the sample suitable to analyse the interplay among various regulatory variables. In the considered study period, the power market reforms have now been concluded with remarkable differences among countries, both in the timing and the intensity of the privatization pattern. The environmental policies also have far overcome the weaknesses of the pilot period of the emission trading scheme (ETS) (2005-2007). Therefore, firm-level dimension allows to take a new micro-level perspective and to enrich the literature on firms' productivity with an integrated analysis of both sector-level and firms-specific variables.

Moreover, the study stresses the core role of the interplay between corporate framework and regulations in affecting the objectives and the decision processes of firms; omitting these interaction variables may introduce significant bias in the estimates of the effects of environmental variables on firm's performance. The asymmetries in electricity regulation cause different incentives that affect the managers' choice regarding the more effective compliance environmental strategy. To depict co-joined effects of environmental regulation with firm specific institutional variables, we include in the model interaction variables.

Most of the non-discretionary variables used to explain the firms performance's do not vary over time. In order to consistently identify the impact of these time-invariant variables, we use the novel two-stage GMM proposed by Kripfganz and Schwarz (2019).

The paper is structured as follows: Section 2 briefly reviews the previous academic contributions, Section 3 presents the analytic method and the data used to estimate the dynamics of performances of the European power generating firms and the impacts of institutional variables. Section 4 provides the main results, while conclusions are exposed in Section 5.

2 Literature

Several studies, focus on the effects of market reforms of power sector with mixed results. Some authors confirm that the standard liberalization prescriptions, such as the privatization of state-own monopoly and the unbundling, promote the performance of the OECD electricity industry in terms of both competition and production (Ajayi et al. 2017; Joskow 2008; Steiner 2001; Triebs and Pollitt 2019). Pollit (2008) highlights instead the two opposite effects of unbundling vertically integrated monopolies. On one hand, unbundling fosters competition and improves operational efficiency; on the other hand, it involves a reduction in the economies of scope and coordination that increase operational costs. Same findings are shown in Zhang et al. (2008) and Erdogdu (2011), who suggest that reform does not necessarily lead to gains in terms of electricity production, capacity utilization and labour productivity in the sector.

Looking at the environmental regulation, a strand of literature maintains that environmental policy, despite some secondary effects (Henisz 2000), boosts the firms' performance as it promotes cost-cutting that reduces or completely offsets the environmental compliance costs (Jaffe et al. 2002; Requante and Unold 2003). Other authors go further, asserting that environmental policies foster innovation that helps firm to expand market shares and achieve the technology leadership (Ambec et al. 2013). Environmental regulation is implemented by using two large classes of instruments: market and non-market tools. Market based policy instruments, such as tradable pollution permits, have appeared more effective in coordinating the emissions abatement activities among firms (Song et al. 2020).[1] Rather than equalizing pollution levels among firms, market-based instruments equalize the marginal abatement cost. However, a strand of literature express concerns for the effects of environmental regulation, even for market-based policy instruments (Levinson and Taylor 2008; Vollebergh and Van der Werf 2014). If market-based tools are not well implemented, firms may not be equipped to fully exploit the incentives mechanisms of market instruments (Mahdiloo et al. 2018). Zhang (2013) show that higher Feed-in Tariff policies have not necessarily yielded to productivity growth in the European power market. Johnstone et al (2017) find that the effects environmental regulation on firms' innovation may turn negative once the level of stringency leaps over a certain threshold. In addition, effects can be far negative according to the plant-specific characteristics such as size and age. Reinhardt (2000) for example notes that companies not necessarily reorganize their internal structure to fully capitalize the cost saving opportunities made available by market-based instruments. This is due to the strictness of environmental standards and controls, in response to which companies have developed rigid processes and skills difficult to convert for fully exploiting the potential benefits of market-based instruments.
This last finding highlights the importance of applying an integrated

[1] No-market tools include environmental standards, commands and controls, technology mandates or maximum emission rates. These policy instruments allowed relatively little flexibility in the means of achieving environmental goals; the main criticism was that they forced firms to take a similar share of pollution control burden and to resort to expensive (and not cost effective) pollution abatement technologies.

approaches that consider the interplay between firm-specific and external institutional variables. Omitting this interaction may introduce significant bias in the estimates of the effects of institutional variables on firm's performance (Ambec and Lanoie 2008). Indeed, the compliance strategies triggered by environmental regulation can be different according to the corporate framework. Firms' choice may range from the purchasing of allowances, to the installing of new emissions abatement technologies or improving of plants' efficiency.
Regarding the link between environmental policy and ownership structure results are contrasting. Beladi and Chao (2006) show that the stringency of environmental regulation leads public firms to reduce pollution by producing less. This is because managers of public plants maximize a social welfare function which internalizes environmental externalities at a shadow prices that reflect the social marginal cost of pollution. Opposite conclusions are found in Wang et al. (2009) where public plants' managers are instructed to maximize fiscal revenues from environmental tax, giving a marginal incentives to increase production (and in turn pollution) that private firms do not have. Earnhart and Lizal (2006) show instead that power plants with higher ownership concentration have higher chance of investing in pollution control technologies.
Fowlie (2010) finds in the US market that regulated firms are more inclined than private firms to capital intensive investments in pollution abatement technologies given the lower financial risk. While state owned utilities can benefit from the cost recovery mechanism of rate adjustment clauses, private firms must instead recover investment costs in the more uncertain wholesale electricity market. Therefore, compliance strategy that relies on purchasing permits can have an option value for private managers compared to public ones.

3 Methodology and Data

In this section we develop the theoretical framework able to estimate the effects of institutional contest on firms' performance. Following a consolidated strand of literature (from Nakano and Managi (2008) to Lin and Chen (2020)), in a first stage the firms' efficiency scores are computed using DEA, then, in a second stage, the efficiency scores are explained using non-discretionary variables that affects the firm's performance, but are not under the control of management.

In subsection 3.1 we show the DEA model applied to compute the firms-specific efficiency indexes from 2010 to 2016. In subsection 3.2 we show the two stage procedure used to estimate the effects of institutional variables on the productivity indexes.

3.1 Computing the efficiency measures

Productivity indexes for the power generating firms spreading in 15 countries are computed using DEA. DEA is a non-parametric method where the efficient frontier is given by the boundary of the production possibility set T that envelops all empirical observations. The frontier represents the best practice technology and produces relevant benchmarking information from a managerial point of view. The efficiency of each firm is indeed given by the “distance” from the input-output vector $(\mathbf{x}_i, y_i) \in T$ to the boundary of the production set T[2]. The computation uses as inputs the number of employees as a proxy of labour, the tangible fixed assets as a proxy of capital, the material costs as a proxy of intermediate inputs used in the power generation process, and the operating revenues as output. Each observation is denoted by $(\boldsymbol{x}_i;\ y_i)^t$ with $i = 1, ..., 655$ refers to the firm and $t = 2010, ..., 2016$ refers to the period. $\boldsymbol{x_i} \in R^q$ with $q = 3$, denotes the vector of the three inputs, while the output is denoted by $y_i \in R$. For each t, the production possibility set, T, is defined by the empirical observations $(\boldsymbol{x}_i, y_i)^t$ gathered in the $N \times 4$ matrix $(\boldsymbol{x}, \boldsymbol{y})^t$:

$$T^t(\boldsymbol{x}, \boldsymbol{y}) = \{(\boldsymbol{x}, \boldsymbol{y})^t \mid \quad \boldsymbol{x}^t\boldsymbol{\lambda} \le \boldsymbol{x}, \quad \boldsymbol{y}^t\boldsymbol{\lambda} \le \boldsymbol{y}, \quad \boldsymbol{\lambda} \ge 0\} \tag{1}$$

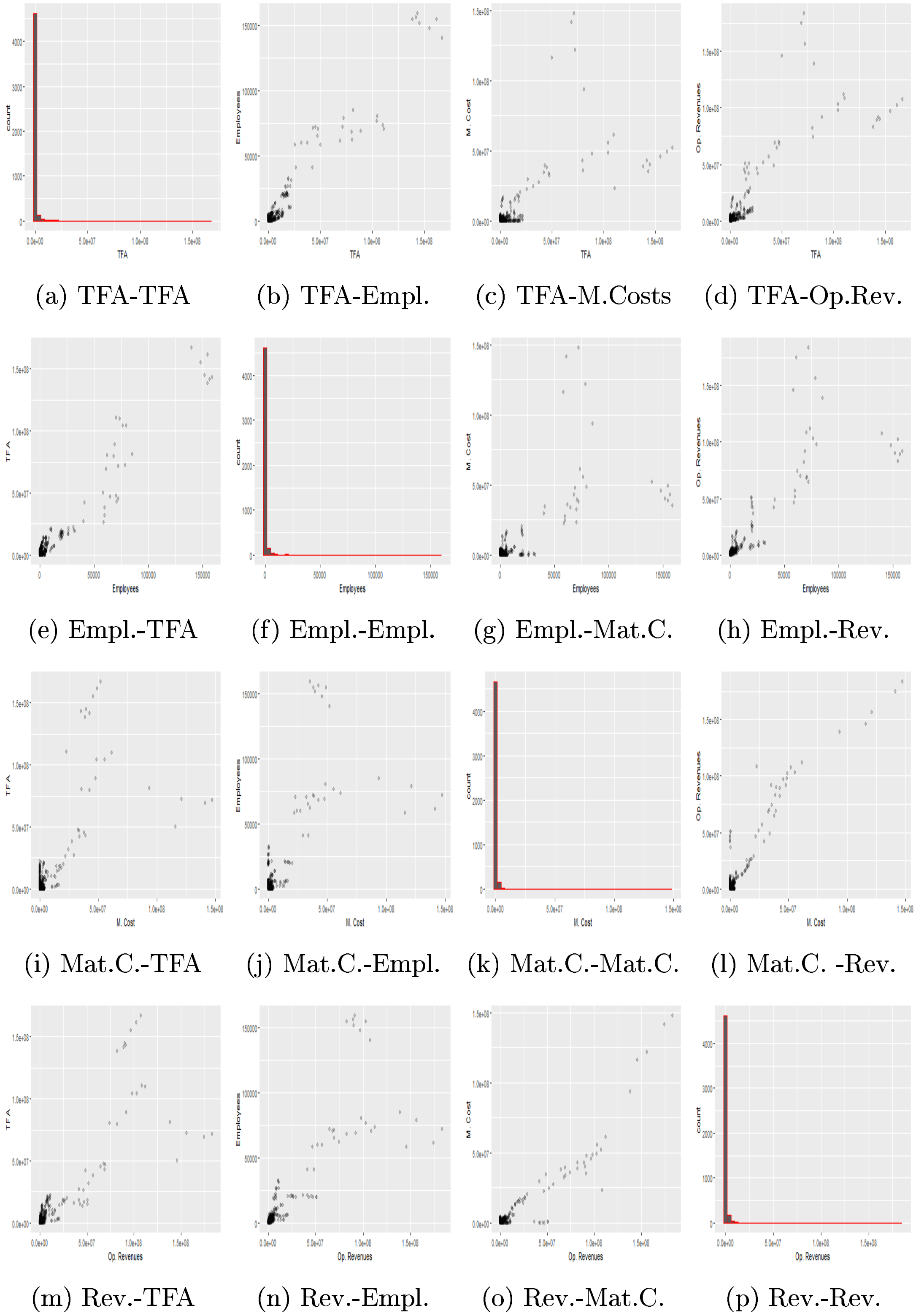
3.1.1 Preliminary Analysis for DEA Model

The first-step preliminary analysis is threefold and i) spots outliers, ii) tests potential endogeneity among inputs and productivity indexes, and iii) identifies which returns to scale define the production possibility set.
It is well known that the distribution of the size of power generating firms is heavily skewed to the right, therefore, prior to estimating firm efficiency, we investigate the presence of outliers that can affect the boundary of the production set and thus lead to biased efficiency estimates. The scatter plot matrix is a useful tool for a preliminary investigation of outliers. Figure 1 clearly shows that data are right skewed. The detection of outliers is then implemented using the traditional data cloud method firstly proposed by Wilson (1993). We omit the 5% of firms as outliers, at the end of the procedure we deal with a panel dataset of 655 firms.

We then investigate the potential endogeneity that may arise among inputs and technical efficiency. This can have implications in the benchmarking analysis and leads to inappropriate performance based recommendations, particularly serious when endogeneity is highly positive. We test endogenenity using the procedure by Peyrache and Coelli (2009), in the Appendix A we describe the test and report the results.

Last, we implement the Simar and Wilson (2020) returns-to-scale test for the output-oriented DEA models between 2010 and 2016, testing the null hypothesis of constant returns to scale against the alternative hypothesis of variable returns to scale. For all cross sections, test rejects the null hypothesis of constant returns to scale at the 0.05 level of significance, ascertaining that the underlying technology set exhibits variable returns to scale. In the Appendix B we report the test statistics and the p-values of the tests between 2010 and 2016.

[2] T^t satisfies all the axioms in Pastor and Lovell (2005) that is: A1) no free lunch, A2) T is bounded, A3) closed and A4) convex set, A5) inputs and output are strong disposable.



(a) TFA-TFA (b) TFA-Empl. (c) TFA-M.Costs (d) TFA-Op.Rev.

(e) Empl.-TFA (f) Empl.-Empl. (g) Empl.-Mat.C. (h) Empl.-Rev.

(i) Mat.C.-TFA (j) Mat.C.-Empl. (k) Mat.C.-Mat.C. (l) Mat.C. -Rev.

(m) Rev.-TFA (n) Rev.-Empl. (o) Rev.-Mat.C. (p) Rev.-Rev.

Figure 1: Scatterplot Matrix of Dataset. 3 inputs: Tangible Fixed Assets, Employees, Material Costs; 1 output: Operating Revenues

3.1.2 The Global Malmquist Index

In this study we use the global MI (Pastor and Lovell 2005) that it is immune to linear program infeasibility problems and it allows technical regress.[3] It is based on a different specification of the best practice technology, the global benchmark frontier, which considers the data of all periods $\{(\boldsymbol{x}, \boldsymbol{y}^t)\}_{t=2010}^{2016}$ belong to the same production possibility set: $T^G = \{\cup_t T^t\}$. The global MI is defined on T^G as follows:[4]

$$\begin{aligned} MI &= \frac{\delta^G((\boldsymbol{x}_i, y_i)^{t+1})}{\delta^G((\boldsymbol{x}_i, y_i)^t)} \\ &= \frac{\delta^{t+1}((\boldsymbol{x}_i, y_i)^{t+1})}{\delta^t((\boldsymbol{x}_i, y_i)^t)} \cdot \left\{ \frac{\delta^G((\boldsymbol{x}_i, y_i)^{t+1})}{\delta^{t+1}((\boldsymbol{x}_i, y_i)^{t+1})} \times \frac{\delta^t((\boldsymbol{x}_i, y_i)^t)}{\delta^G((\boldsymbol{x}_i, y_i)^t)} \right\} \\ &= \underbrace{\frac{\delta^{t+1}((\boldsymbol{x}_i, y_i)^{t+1})}{\delta^t((\boldsymbol{x}_i, y_i)^t)}}_{Eff.} \cdot \underbrace{\left\{ \frac{BPG^{G,t+1}((\boldsymbol{x}_i, y_i)^{t+1})}{BPG^{G,t}((\boldsymbol{x}_i, y_i)^t)} \right\}}_{Tech.} \end{aligned} \tag{2}$$

where δ defines the output oriented distance function. $\delta^G((\boldsymbol{x}, y)^t) = inf\{\phi > 0 \mid (\boldsymbol{x}, y/\phi)^t \in T^G\}$ reflects the gap between the observation and the global benchmark frontier, while $\delta^s((\boldsymbol{x}, \boldsymbol{y})^r) = inf\{\phi > 0 \mid (\boldsymbol{x}, y/\phi)^r \in T^s; \quad s, r = t, t+1\}$ reflects the gap between the observation and the contemporaneous frontier.[5] Like the standard MI, the global MI can be decomposed into the two usual components $Eff.$ and $Tech.$, but this latter provides a new measure of technical change and represents the change in the best practice gap BPG between the periods t and $t+1$. $BPG^{G,s}$ is the best practice gap between the global benchmark frontier T^G and the contemporaneous frontier T^s measured along rays $(\boldsymbol{x}, \boldsymbol{y})^s$, $s = t, t+1$. For all the three indexes (MI, $Eff.$ and $Tech$), values greater than one signal progress in the efficiency, while values equal or lower than one indicate the non variation or the deterioration of efficiency, respectively.
The computed global MI constitutes the dependent variable used in the next panel linear regression model.

3.2 Dynamic Panel linear model

In this section we show the second step of the estimation procedure where a reduced form equation is applied to explain the MI as a function of the institutional variables.

[3]The other specific features of the global MI are that it satisfies circularity condition and generates a single measure of productivity change.
[4]Since there is only one global benchmark technology, there is no need to resort to the geometric mean usually applied for the standard MI.
[5]We assume output orientation, where inputs are predetermined and output is expanded proportionally.

3.2.1 The Separability Tests

Prior to running a second-stage regression using DEA scores, we check whether the separability condition holds (Daraio et al. 2018) that is necessary for applying the second stage regressions. The presence of environmental variables raises indeed the question of how these external variables affect the production process. Conceivably, the environmental variables might either affect the distribution of efficiency among firms, or the production possibilities of firms. The separability condition is very strong and restrictive, under the separability condition the environmental variables in fact influence neither the shape nor the level of the boundary of the production possibility set, their effects on the production process are only through the distribution of the inefficiencies. If the separability condition holds, that is, if the environmental variables do not impact the production possibility set and its boundary, it is meaningful to measure the efficiency of firms by their distances to the efficient frontier. If this condition is violated, not only the second-stage regressions are meaningless, but also the first-stage efficiency indexes are misleading.
The test involves randomly splitting the sample into different independent subsamples, computing the unconditional and conditional (on the environmental variable) efficiency indexes and comparing the mean of the unconditional efficiency estimates, where separability is imposed, with the mean of the conditional efficiency estimates. If the separability assumption holds, then the unconditional and conditional efficiency estimators converge to the same object and the unconditional DEA scores can be used in a second stage regression. In our case, we found that the separability condition holds (see Appendix D), allowing for the two-stage GMM estimation.

3.2.2 The Two Stage GMM Estimation

The set of environmental variables employed in the dynamic linear model is composite, we have already mentioned that they can be differentiated in internal and external institutional variables, but, further, they have to be distinguished between time-varying and time-invariant variables for the empirical estimation. This difference plays a crucial role in the choice of the estimation procedure. Starting from the assumptions of Blundell and Bond (1998), the dynamic panel model is the following:

$$
\begin{aligned}
y_{i,t} &= \rho y_{i,t-1} + \mathbf{x}_{i,t}\boldsymbol{\beta} + \mathbf{f}_{i,t}\boldsymbol{\gamma} + e_{i,t} \\
e_{i,t} &= \alpha_i + u_{i,t}
\end{aligned}
\tag{3}
$$

where i and t refer to the firms and the periods, respectively, $y_{i,t}$ is the technical efficiency, $\mathbf{x}_{i,t}$ contains the time-varying variables, the vector $\mathbf{f}_i$ contains instead the time-invariant variables, while the error term $e_{i,t}$ is usually decomposed in the fixed effect α_i and the idiosincratic error terms $u_{i,t}$.
The traditional "fixed-effects" procedures are not applicable because the time

invariant regressors are perfectly collinear with the unit-specific dummy variable that make hard to disentangle the effects of the observed and unobserved time-invariant heterogeneity. Moreover, when the time dimension is too short as in the present study, fixed effect estimators suffer from the familiar Nickell (1981) bias in dynamic panel data models. Conventional GMM estimators are frequently used for "short T, large N" panels, as they allow for fixed effect, heteroskedasticity, autocorrelation, and endogeneity of the explanatory variables (Arellano and Bond 1991; Blundell and Bond 1998). However, they require strong orthogonality assumptions on the instruments. If the exogeneity conditions do not hold, all coefficient estimates, including those of time-varying regressors, might be inconsistent. Therefore, we follow the estimation procedure proposed by Kripfganz and Schwarz (2019) that it is specific for dynamic panel linear models with a short time dimension and it focuses on the identification of coefficient of time-invariant variables in the presence of unobserved fixed effects. The method is based on a sequential procedure which provides valuable robustness against mispecified exogeneity assumptions.

The first stage consistently estimates only the coefficients of the time-varying regressors (ρ and $\boldsymbol{\beta}$) by subsuming the time-invariant variables under the unit-specific effects, $\eta_i = \mathbf{f}_i\boldsymbol{\gamma} + \alpha_i$ as follows:

$$\begin{aligned} y_{i,t} &= \rho y_{i,t-1} + \mathbf{x}_{i,t}\boldsymbol{\beta} + \bar{\eta} + e_{i,t} \\ e_{i,t} &= \eta_i - \bar{\eta} + u_{i,t} \end{aligned} \tag{4}$$

In this first stage it is possible to apply different estimators.[6] We apply the Blundell and Bond system estimator that uses as instruments for the endogenous variable $y_{i,t-1}$ in the level equation the lagged first differences (starting from $t-2$); we obtain coefficient estimates $\tilde{\rho}$ and $\tilde{\boldsymbol{\beta}}$.[7]
In the second stage, we regress the first-stage residuals on the time-invariant variables.

$$\begin{aligned} y_{i,t} - \tilde{\rho} y_{i,t-1} - \mathbf{x'_{i,t}}\tilde{\boldsymbol{\beta}} &= \mathbf{f'_i}\gamma + v_{i,t} \\ v_{i,t} &= \alpha_i + u_{i,t} - (\tilde{\rho} - \rho) y_{i,t-1} - \mathbf{x_{i,t}}'(\tilde{\boldsymbol{\beta}} - \boldsymbol{\beta}). \end{aligned} \tag{5}$$

The first-stage estimation error shows up in the error term $v_i t$, that is, the second stage error $v_{i,t}$ is corrected to account for the first-stage estimation error term. Since $(\tilde{\rho}, \tilde{\boldsymbol{\beta}})$ are consistent estimators for the first stage, the second stage moment conditions can be still defined in terms of $e_{i,t}$ instead of $v_{i,t}$.[8] The standard-error correction is one of the main advantage of this inference model.

[6] This includes the QML estimator of Hsiao et al (2002), the GMM estimators with the linear moment conditions of Arellano and Bond (1991) and Blundell and Bond (1998), and the GMM estimators based on the non-linear moment conditions of Ahn and Schmidt (1995). In contrast, the conventional fixed-effects estimator it is inconsistent in dynamic panel data models when T is fixed.

[7] See Blundell and Bond (1998) and Blundell et al. (2001).

[8] The reader is referred to Kripfganz and Schwarz (2019) for the theoretical framework and demonstration.

The other advantage of the two-stage GMM procedure is the invariance of the first-stage time-varying estimates regardless the potentially wrong exogeneity assumptions on the instruments for the time-invariant variables. This methodology can use in fact any first-stage consistent estimator for the coefficients of time-varying variables, without relying on the consistency of the second-stage estimates of the coefficients of the time-invariant variables.

To further increase the efficiency of the estimates, we apply the two-step GMM that uses the Windmeijer-corrected robust standard errors (Windmeijer 2005).[9]

3.3 Data

In the first stage the technical efficiency indexes are computed using the accounting company data of ORBIS database.[10] Table 1 provides the main summary statistics for the balanced panel dataset used in the first step.

Table 1: Summary Statistics of Input and Ouput used in DEA Analysis by Country

Variable		Mean	Std. Dev.	Min	Max	Obs.
Tangible Fix. Assets	overall	137336.1	377829.2	0.2076112	5112488	N = 4585
	between		363571.9	3.309646	3461099	n = 655
	within		103650.3	-879046.6	2564536	T = 7
Employees	overall	133.3876	341.2456	1	5129	N = 4585
	between		335.1141	1	3096.714	n = 655
	within		65.52958	-727.8981	2165.673	T = 7
Material Costs	overall	115687.1	342087.2	0.0073787	3770278	N = 4585
	between		279359.9	0.5380906	1877066	n = 655
	within		197696.3	-1464174	3191247	T = 7
Op. Revenues	overall	142279.3	361130.6	0.0674624	3589887	N = 4585
	between		345873	19.14454	2606691	n = 655
	within		104612.3	-964278.6	1684598	T = 7

Table decomposes observation $x_{i,t}$ into a between, $\bar{x}_i$, and within, $x_{i,t} - \bar{x}_i + \bar{x}$, part. Note that the overall mean $\bar{x}$ has to be added back to $x_{i,t}$ to make results comparable. The overall and the within statistics are computed over the whole panel dataset of 4585 observations. The between statistics are instead computed over the 655 firms and the number of years a firms is observed is 7. Table also reports minimums and maximums. Rows corresponding to "overall" report the minimum and the maximum of the whole panel dataset. Rows corresponding to "between" report the minimum and the maximum values of

[9] As all instruments are internal, a necessary condition for the identification of all coefficients in equation (3) is that $K_x(T+1) > K_f$ where K_x states for the time-varying exogenous regressors and K_f states for the endogenous time-invariant variables.

[10] ORBIS is a commercial database of Bureau van Dijk which provides information on European-based firms' legal aspects and location, industrial activity, NACE sector, employment, sales, value added, capital formation. Data originated from company reports collected by different providers specific to each country.

the averages of each panel. Statistics corresponding to the rows "within" can show negative values. This is because the within number refers to the deviation from each individual's average, and naturally, some of those deviations must be negative.

Focusing on the Op. Revenues output, to avoid the bias due to the country-specific price assessments, the operating revenues, provided in current prices, were converted into constant prices by using sectoral GDP deflators (Eurostat National Accounts based on the year 2010). Here it is enough to mention that the economic data provided by ORBIS are rather patchy and their quality is heterogeneous across countries. In particular: i) we exclude firms for which employment, tangible fixed assets, material costs or operating revenues were missing or not positive; ii) we drop outliers. As a consequence, from the raw dataset of 2400 companies, we select only 655 firms.

Looking at the GMM procedure, the first stage time-varying explanatory variables are:

- *GDP-per-capita*: the GDP-per-capita in constant prices (base-year 2010), it is sourced from OECD database[11].
- *Balance Trade*: the balance trade of national electricity consumption, it is sourced from Eurostat Energy Database[12]. It expresses the openness of the electricity sector to trade and proxies the exposure of the sector to cross-border competition.
- *Retailer Ratio*: the ratio between the numbers of main retailers and the total numbers of retailers is used to identify the market structure of the downstream sector.[13] Higher values of this ratio denote lower degrees of concentration in the downstream electricity market. This variable depicts the likelihood of buyers to exercise market power and adopt collusive behaviours that can erode the operating revenues of power generating firms (especially in the electricity sector, where homogeneous blocks of energy are exchanges).

The time invariant variables are divided in two groups: the OECD's regulatory indexes, identifying the external institutional variables, and the firm-specific variables. In the first group we include the *Ownership Index* and the Market Structure to define the stringency of market regulation. The stringency of environmental regulation is instead expressed by three OECD indexes: *EPS, Market-EPS* and *ETS*. The OECD indexes are listed as follow:

- *Ownership Index*: it measures the presence of public ownership in the power sector, it ranges between 0 and 6 and it increases as the share owned, either directly or indirectly, by the government in the largest firm increases.

[11] https://stats.oecd.org/Index.aspx?DataSetCode=PDB_LV
[12] Data can be downloaded from the following link: https://appsso.eurostat.ec.europa.eu/nui/show.\do?dataset=nrg_te_eh&lang=en.
[13] Data are sourced from EU Energy Market reports (2011, 2014).

- *Market Structure*: it defines the rate of competition in the industry according to the market share of the largest electricity company. It goes from 0 to 6 with higher values associated to a greater share held by the incumbent. [14]
- *EPS*: this index defines the degree to which environmental policy puts an explicit or implicit price on polluting or environmentally harmful behaviours of the whole economy. It ranges between 0 and 6, with higher values indicating more stringent environmental regulations. EPS is a multidimensional index based on the degree of stringency of 14 environmental policy instruments. *EPS* can be decomposed in two elements: the market-based and non market-based indexes.[15]
- *Market-EPS*: it is the *EPS*'s sub-component which measures the stringency of the market-based policy instruments, which assign an explicit price to the negative environmental externalities. Also the *Market-EPS* index ranges between 0 and 6 and it can be in turn decomposed in specific sub-indexes defining the stringency of a particular market-based policy instrument.
- *ETS*: this *Market-EPS*'s sub-index defines the stringency of the emission trading scheme and it is given by the yearly average of allowance prices.

The internal institutional variables refer to the firm ownership structure: *Concentration* and *Dummy Public*.

- *Own. Dispersion*: the ownership dispersion is proxied by the BvD Independence indicator from the ORBIS database. This index measures the independence of management from ownership, it considers the number of shareholders and the percentage of their individual and collective holdings. It is denoted by letters A, B, C, D and U, each signifying a different degree of ownership dispersion, expect for U designating the unknown situation. Moving from A to D designates more concentrated companies from the ownership perspective.[16]
- *Dummy Public*: the dummy variable assumes value equal to one if the firm is a state owned utility.

To depict the interplay among the different institutional variables we interact the environmental regulatory indexes with the corporate variables and include them in the model. Table 2 collects the summary statistics of the variable used in the second step GMM procedure.

[14] Both indexes can be downloaded from the following link: https://www.oecd-ilibrary.org/economics/data/oecd-product-market-regulation-statistics_pmr-data-en.

[15] Data can be downloaded from the following link: https://www.oecd-ilibrary.org/environment/data/oecd-environment-statistics/environmental-policy-stringency-index_2bc0bb80-en.

[16] We factorize the BvD Independence indicator from two to ten, giving higher values to firms with low degree of concentration.

Table 2: Summary Statistics of Explanatory Variables used in the two-stage GMM Procedure

Variable		Mean	Std. Dev.	Min	Max	Obs.
MI	overall	1.102369	0.8999282	0	21.28866	N=3930
	between		0.3502181	0.1874182	4.461793	n=655
	within		0.8290803	-3.261534	17.92923	T=6
Balance Trade	overall	-4350.145	26537.96	-46378	67190	N=3930
	between		25599.62	-44204.5	51893.5	n=655
	within		7053.843	-26188.81	18328.19	T=6
GDP-per-capita	overall	31492.59	9835.309	10682.3	51397.12	N=3930
	between		9815.82	11537.27	49438.99	n=655
	within		711.0529	29841.02	33450.71	T=6
Retailers Ratio	overall	0.0562732	0.1060058	0.003	0.6153846	N=3930
	between		0.1047508	0.0033333	0.4967949	n=655
	within		0.0166875	-0.0030216	0.174863	T=6
Public Ownership Index	overall	1.611705	1.728901	0	6	N=3930
	between		1.725427	0	6	n=655
	within		0.1256521	0.8267048	2.396705	T=6
Market Structure Index	overall	0.2377863	0.6255135	0	4.5	N=3930
	between		0.6147428	0	3.25	n=655
	within		0.117641	-0.0122137	1.487786	T=6
EPS	overall	2.878547	0.4441842	2.13	4.13	N=3930
	between		0.4009383	2.221667	3.693333	n=655
	within		0.1917097	2.293547	3.320214	T=6
Market-EPS	overall	2.060809	0.6218771	1.05	3.98	N=3930
	between		0.587984	1.248333	3.606667	n=655
	within		0.2035829	1.685809	2.692476	T=6
ETS	overall	1.818473	1.270058	0.4	5.2	N=3930
	between		1.142349	0.9333333	4.7	n=655
	within		0.5565486	0.8851399	2.88514	T=6
Own. Dispersion	overall	4.516794	1.727334	2	10	N=3930
	between		1.728434	2	10	n=655
	within		0	4.516794	4.516794	T=6
Dummy Public	overall	0.1740458	0.3791971	0	1	N=3930
	between		0.3794386	0	1	n=655
	within		0	0.1740458	0.1740458	T=6

4 Results

First, we compute the technical efficiency estimates for the 655 power generating firms between 2010-2016. In the Appendix C, table C.1 reports the summary statistics of the global MI aggregated by country.
Second, we estimate equation (3) using the two-stage GMM procedure. Tables 3-4 present the coefficient estimates for six models. Models differ in the time-invariant variables used as regressors in the second stage equation, while the first stage equation is always the same. Models (1a) (2a) and (3a) use as market regulatory indexes the *Market Structure* index and change the index expressing the stringency of environmental regulation, the *EPS*, the *Market EPS* and the *ETS*, respectively. Models (1b) (2b) (3b) replace *Market Structure* index with the *Ownership Index*. All models employ the *Dummy Public* and *Own. Dispersion* as time-invariant internal institutional variables. Table

4 shows results for the models which add to the formers the interaction variables catching the interplay between the environmental policy indexes and the firm-specific features.[17]

4.1 First Stage GMM Results

In both tables 3-4 the autoregressive parameter is positive and lower than one, defining a stable dynamic pattern for the global MI.[18]
Looking at the time-varying variables, *GDP-per-capita* shows positive and significant coefficient as well as *Balance Trade*. The productivity of power generating plants are thus spurred by a positive electricity balance trade, that expresses the energy self-sufficiency of a country and its ability to meet domestic demand.
As expected, the variable proxying the degree of retailers' sector concentration is positive correlated with productivity. When the *Retailers' Ratio* increases, the number of operators in the downstream sector increases and, in turn, their market power decreases with positive effects in the revenue performance of power generation sector. This result is also consistent with the findings in Bahçe and Taymaz (2008), who show that competition in the downstream sector, where an increasing number of both small and large retailers can directly purchase electricity or change their electricity suppliers, stimulates the performance of the up-stream sector.

4.2 Second Stage GMM Results, the direct effects of institutional variables

Looking at the second stage estimation results in table 3, it emerges the positive effects of the *Ownership Index* on spurring productivity (ranging between 0.0115 and 0.0271). Same positive effects are expressed by the signs of the coefficients referring to the *Market Structure* index, which lies between 0.0625 and 0.0746. Recalling that high values of the two indexes are associated with low degrees of privatization and competition, results suggest that market reforms have shrunk the performance of European power sector in term of global MI. This result is consistent with the findings in Zhang et al. (2008), Pollit (2008), and Erdogdu (2011), who show that privatization and unbundling lead to the undesired effect of a decline of the performance due to the reduction in coordination and economies of scope.
Coefficients referring to the stringency of environmental regulation are always negative (when significant), suggesting that the stringency of environmental regulation may shrink the global MI. In particular, the estimates of the EPS coefficient in models (1a) and (1b) range between -0.0509 and -0.0619. It

[17] Using global MI as dependent variable and the lagged dependent variable as regressors obliged us to discard two time periods; thus, the initial sample of 4585 observations was reduced to 3275 observations.

[18] As already mentioned, the two-stage GMM procedure has the great advantage of the invariance of the first-stage estimates over incorrect exogeneity assumptions on the time-invariant regressors, providing more robust results to such potential misspecification.

Table 3: Regression Results for MI

	(1a) MI	(1.b) MI	(1.c) MI	(2.a) MI	(2.b) MI	(2.c) MI
_first						
L.MI	0.0422*	0.0422*	0.0422*	0.0422*	0.0422*	0.0422*
	(1.78)	(1.78)	(1.78)	(1.78)	(1.78)	(1.78)
Balance Trade	0.00282***	0.00282***	0.00282***	0.00282***	0.00282***	0.00282***
	(2.76)	(2.76)	(2.76)	(2.76)	(2.76)	(2.76)
Retailers Ratio	0.858***	0.858***	0.858***	0.858***	0.858***	0.858***
	(6.54)	(6.54)	(6.54)	(6.54)	(6.54)	(6.54)
GDP-per-capita	0.0000273***	0.0000273***	0.0000273***	0.0000273***	0.0000273***	0.0000273***
	(32.32)	(32.32)	(32.32)	(32.32)	(32.32)	(32.32)
_second						
Market Structure Index	0.0726***	0.0625***	0.0746***			
	(3.19)	(2.78)	(3.41)			
EPS	-0.0509***			-0.0619***		
	(-3.49)			(-4.03)		
Dummy Public	-0.0615**	-0.104***	-0.0947***	-0.0494*	-0.0970***	-0.0907***
	(-1.99)	(-3.51)	(-3.15)	(-1.68)	(-3.36)	(-3.19)
Own. Dispersion	0.0501***	0.0214***	0.0400***	0.0514***	0.0216***	0.0377***
	(5.28)	(2.71)	(7.30)	(5.40)	(2.74)	(6.54)
Market-EPS		0.00569			0.00243	
		(0.34)			(0.14)	
ETS			-0.0536***			-0.0624***
			(-5.05)			(-5.61)
Public Ownership Index				0.0246**	0.0115	0.0271***
				(2.41)	(1.10)	(2.92)
Observations	3275	3275	3275	3275	3275	3275

Note: t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Regression Results for the model with the cross-effects. MI

	(1.a) MI	(1.b) MI	(1.c) MI	(2.a) MI	(2.b) MI	(2.c) MI
_first						
L.MI	0.0422*	0.0422*	0.0422*	0.0422*	0.0422*	0.0422*
	(1.78)	(1.78)	(1.78)	(1.78)	(1.78)	(1.78)
Balance Trade	0.00282***	0.00282***	0.00282***	0.00282***	0.00282***	0.00282***
	(2.76)	(2.76)	(2.76)	(2.76)	(2.76)	(2.76)
Retailers Ratio	0.858***	0.858***	0.858***	0.858***	0.858***	0.858***
	(6.54)	(6.54)	(6.54)	(6.54)	(6.54)	(6.54)
GDP-per-capita	0.0000273***	0.0000273***	0.0000273***	0.0000273***	0.0000273***	0.0000273***
	(32.32)	(32.32)	(32.32)	(32.32)	(32.32)	(32.32)
_second						
Market Structure Index	0.0221	0.0547**	0.0666***			
	(0.96)	(2.48)	(3.18)			
EPS	0.0209			0.0146		
	(1.18)			(0.79)		
Dummy Public	0.0390	-0.304***	-0.276***	-0.0193	-0.305***	-0.264***
	(0.17)	(-2.94)	(-5.43)	(-0.08)	(-2.91)	(-5.36)
Own. Dispersion	0.230***	0.0391***	0.0519***	0.231***	0.0407***	0.0491***
	(13.08)	(3.34)	(8.60)	(13.04)	(3.43)	(7.64)
Dummy Public*EPS	-0.0448			-0.0233		
	(-0.59)			(-0.31)		
Own. Dispersion*EPS	-0.0758***			-0.0760***		
	(-10.00)			(-9.98)		
Market-EPS		0.0215			0.0220	
		(0.81)			(0.80)	
Dummy Public*Mkt-EPS		0.103*			0.106*	
		(1.73)			(1.76)	
Own. Dispersion*Mkt-EPS		-0.0115			-0.0124	
		(-1.37)			(-1.49)	
ETS			-0.0132			-0.0265
			(-0.55)			(-1.03)
Dummy Public*ETS			0.113***			0.110***
			(3.05)			(3.13)
Own. Dispersion*ETS			-0.0146***			-0.0126**
			(-2.58)			(-2.17)
Public Ownership Index				0.0119	0.00746	0.0210**
				(1.24)	(0.70)	(2.22)
Observations	3275	3275	3275	3275	3275	3275

Note: t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

means that an increase by one in the stringency of this index causes a reduction in productivity by more than 5%. Market-EPS index is not significant in both models, but when we shift to the more specific ETS index, that accounts only for the stringency of the emission trading scheme, the coefficient estimates are significant and negative (models (3a)-(3b)). This contrasts a traditional strand of literature that have long ascertained that market based instruments, such as emissions permits, could more efficiently coordinate pollution abatement activities among firms (Baumol and Oates 1988; Montgomery 1972). Nevertheless, these finding corroborate the concerns for market-based policy instruments expressed by more recent studies (Levinson and Taylor 2008; Reinhardt 2000; Vollebergh and Van der Werf 2014). If market based policy instruments are not well implemented, firms may not be well equipped to fully exploit the incentives mechanisms of market instruments environmental policy instruments.

Looking at the firm-specific institutional variables, the *Own. Dispersion*'s coefficient is significant and positive in all models: widely held companies perform better than firms with concentrated ownership. This confirms the results exposed in Benedsen and Nielsen (2010), Wang and Shailer (2015) and Aluchna and Kaminski (2017), where companies with widespread ownership are more likely to attract external capital since they have been perceived with lower financial risk.[19] Moreover, the results are in line with the common assumption that companies with widespread ownership rely on managerial labour market to employ higher quality directors, rather than entrench shareholders in the board position. This mechanism enforces the corporate governance as well as the performance (Claessens et al. 2002). Regarding the *Dummy Public*, the coefficient is negative, showing that state-owned utilities have lower performance compared to their private counterparts since they may also pursue social objective that is wider than the simple profit maximization. This finding is consistent with the literature arguing that state-owned utilities face higher inefficiency compared to private enterprises because of the weaker budget constraints, the lack of any risk of bankruptcy or hostile takeover (La Porta et al. 1998; Vickers and Yarrow 1998), the political interference and the risk of political capture by private interests (Shleifer and Vishny 2002).

4.3 Second Stage GMM Results, the cross-effects of institutional variables

The interplays among institutional variables involves the cross-effects between the environmental regulation and the internal institutional features related to the ownership structure. Therefore, in each of the former models, we add two interaction variables, by multiplying the *Own. Dispersion* and the *Dummy Public* for the specific environmental regulatory index. Adding the interaction variables does not change the signs of the coefficients related to the direct

[19] Recall that high values of the index state for low levels of concentration.

effects of the explanatory variable, signalling that the models are robust.
Focusing on the interplay between *Own. Dispersion* and the environmental OECD indexes, all variables show a negative effect. It means the an increase in the stringency of environmental regulation causes more negative effects in those firms with low degrees of concentration. These findings are consistent with the empirical results of Earnhart and Lizal (2006) who show that firms with widespread ownership, that operates in restructured markets, face higher cost of capital that makes the securing financing for investments in pollution-control technologies relative more costly.
Looking at the interplay between the *Dummy Public* and the environmental policy, only the interactions with the market-based policy indexes (Market-EPS and ETS) are significant, with positive coefficients. It means that state-owned utilities seem to better react to a stricter market-based environmental regulation. The reason of these empirical findings can be provided by Fowlie (2010) who states that regulated firms are more inclined to capital intensive investments in pollution abatement technologies because they face a risk lower than that faced by their private counterparts: they are in fact guaranteed to recover investment costs by public regulator. Absent cost recovery guarantees, the consequence of making capital investments in pollution control equipments are higher uncertain since plants must recover the investment costs in the wholesale electricity market.

5 Conclusions

This study intended to investigate the main factors affecting the compliance strategies and the productivity of companies operating in the European electricity sector, that in the last two decades has undertaken a deep wave of market and environmental reforms, being one of the most strategic sector. The analysis encompassed both internal and external institutional factors that affect the firm level decision process. We were aware of the complexity of such environmental framework that strongly requires coordination among the multiple policy instruments involved: profit opportunities and incentives mechanisms are shaped by the country-specific implementation systems which determine divergent corporate strategies. We applied a benchmarking analysis to compute the firms' efficiency performance using the global MI to address the infeasibility problems of traditional MI. The two stage GMM method has then allowed to consistently estimate, in a more robust way, the effects of institutional time-invariant variables. In order to address the problem and capture the complex phenomena in the relationship between institutional framework and performance, we used a manifold set of variables, trying to catch the interdependence and the cross-effects among different institutional factors.
We showed that *Ownership Index* and *Market Structure*, expressing the degree liberalization, positively affects power plants' productivity.
The stringency of environmental regulation has been expressed by different indexes that gradually become more specific. All indexes have negative

marginal effects on firms' performance, in particular, when focus lies on *ETS*, the reduction in the productivity is more significant.
Regarding the internal factors, the direct effect of *Dummy Public* on the global MI of the is negative; that corroborated the common hypothesis that state-owned utilities maximized an objective function wider than the simple profit, that could include also the negative environmental externalities. The coefficient estimates of the variable *Own. Dispersion* revealed instead the positive link between a widespread ownership structure and the firm's productivity: widely held companies perform better than firms with concentrated ownership. The cross-effects among environmental policy indexes and the corporate ownership factors, used to depict the interplay among multiple institutional features, suggested composite results: firms with public or concentrated ownership better react to stricter environmental policies, contrasting the negative direct effects of environmental regulation. These last results highlighted a crucial policy implication. The policy design should take into account that different linkages among environmental policy instruments and the corporate framework result in different incentive mechanisms, which have biased effects on the firms' decision processes as well as on the firms' productivity. Therefore, coordination among the main variables defining the institutional environment is needed in order to either avoid or at least to mitigate the negative effects of the stringency of regulation. Moreover, environmental regulations should be gauged according to the firm-specific corporate framework that affects the firms performance.

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Appendix A Endogeneity Tests

In this appendix we shows the Peyrache and Coelli (2009) procedure to test endogeneity among inputs, outputs and efficiency indexes. Within a production process endogeneity occurs when the efficiency is not exogenously distributed with respect to some inputs or, in other words, when there is a correlation between the inputs and the efficiency indexes (Bifulco and Bretschneider 2001). Peyrache and Coelli (2009) start with the stochastic representation of the production possibility set[20] and propose a semi-parametric Hausman-type asymptotic test for the non-correlation of all inputs and outputs included in the DEA model.[21]

[20]For more details see Kumbhakar and Lowell (2000)

[21]A different approach addresses the endogeneity problem using instrumental variables (Ackerberg et al. 2007; Atkinson and Primont 2002; Mayston 2017; Sickles et al. 2002; Wooldridge 2009),

Let $i = 1, ..., N$ the number of firms, $\boldsymbol{x} \in R^{(q \times N)}$ the matrix of q inputs, $\boldsymbol{y} \in R^{(p \times N)}$ the matrix of p outputs, and $\boldsymbol{\delta} \in R^N$ the vector of the output oriented efficiency scores derived from DEA, the notion of non-correlation between the efficiency scores, the inputs and outputs is defined as:
Definition 1: The efficiency score δ is uncorrelated with $\boldsymbol{x}$ and $\boldsymbol{y}$ if and only if $E(\delta \mid \boldsymbol{x}, \boldsymbol{y}) = E(\delta)$.
Peyrache and Coelli (2009) construct the Wald statistic using a weighted average estimators ϕ for the technical efficiencies' average. A generic weighted function ϕ can be written as follows:

$$\phi = \sum_{i=1}^{N} w_i \delta_i, \quad \sum_{i=1}^{N} w_i = 1 \tag{A.1}$$

where δ_i is the efficiency index of the observation i and w_i is the random weight defined as sample function $w_i(\boldsymbol{x}_i, \boldsymbol{y}_i) = {}^{g(\boldsymbol{x}_i, \boldsymbol{y}_i)}/\sum_{i=1}^{N} g(\boldsymbol{x}_i, \boldsymbol{y}_i)$, $i = 1, ..., N$ and $g : R^{q+p} \to R$ is a generic function. Rewriting (A.1) as:

$$\phi = \sum_{i=1}^{N} \left(\frac{g(\boldsymbol{x}_i, \boldsymbol{y}_i)}{\sum_{i=1}^{N} g(\boldsymbol{x}_i, \boldsymbol{y}_i)} \right) \delta_i, \tag{A.2}$$

ϕ is a consistent estimator of the efficiency indexes average only if there is not correlation between $g(\cdot)$ and δ.

Proposition 1 *If the efficiency score δ is statistically uncorrelated from the arguments of the function $g(\boldsymbol{x}, \boldsymbol{y})$, then the statistic ϕ satisfies the consistency property $\phi \to^P E(\delta)$.*

Proof See Peyrache and Coelli (2009), pp 649. □

Peyrache and Coelli (2009) simplify the function $g(\cdot)$ considering it directly equal to one of the inputs $\boldsymbol{x}^s, s = 1, ..., q$ or one of the outputs $\boldsymbol{y}^m, m = 1, ..., p$. Given the input x^s, the function ϕ_s^{Inp} for the input x^s is given by:

$$\phi_s = \sum_{i=1}^{N} \left(\frac{x_i^s \delta_i}{\sum_{i=1}^{N} x_i^s} \right), \quad s = 1, ..., q \tag{A.3}$$

but it implies the availability of external instruments or other sources of information such as input-output prices.

Given the output y^m with $m = 1, ..., p$, the function ϕ_m^{Out} for the output y^m is given by:

$$\phi_m^{Out} \sum_{i=1}^{N} \left(\frac{y_i^m \delta_i}{\sum_{i=1}^{N} y_i^m} \right), \quad m = 1, ..., p \tag{A.4}$$

In this way, it is possible to define $q+p$ different statistics for all the inputs and the outputs in the model. From the central limit theorem, the sample mean of the efficiency $\bar{\delta} = \sum_{i=1}^{N} \delta_i / N$ is a consistent estimator of $E(\delta)$, and from Proposition 1, (A.3) and (A.4) are also consistent estimators of δ under the hypothesis of non-correlation. Consequently, the differences $[\phi_s^{Inp} - \bar{\delta}]$ and $[\phi_m^{Out} - \bar{\delta}]$ for $s = 1, ..., q$ and $m = 1, ..., p$ converge in probability to zero if non-correlation holds. Finally, by defining $\boldsymbol{d} = \left[(\phi_1^{Inp} - \bar{\delta}), .., (\phi_q^{Inp} - \bar{\delta}), (\phi_1^{Out} - \bar{\delta}), ..., \phi_p^{Out} - \bar{\delta} \right]$, it is possible to check non-correlation by means of the following test:

$$\begin{cases} H_0 : & E(\boldsymbol{d}) = \boldsymbol{0}_{p+q} \\ H_1 : & E(\boldsymbol{d}) \neq \boldsymbol{0}_{p+q} \end{cases} \tag{A.5}$$

A.5 can be solved through the Wald statistic $W = \boldsymbol{d}'[\hat{Var}(\boldsymbol{d})]^{-1}\boldsymbol{d}$ which is asymptotically distributed as a chi-square with $p + q$ degrees of freedom.
The procedure must be executed in three steps. First, the individual efficiency estimates δ_i are derived from the DEA.[22] Second, the covariance matrix $Var(\boldsymbol{d})$ is estimated using bootstrap. In the final third step, the Wald statistic is computed and compared with the corresponding chi-square. For each year of the study period, we perform the test using 1000 iterations for the bootstrap procedure. Table A.1 shows the p-values of the tests applied for each period. For all years, with significance level $\alpha = 0.05$ we can not reject the null hypothesis of no endogeneity, which leads to assume inputs and output exogenous with respect to the technical efficiency.

[22] Although the δ_i can not be the true efficiencies, the DEA estimator using the radial (Shephard) approach, is consistent, and, therefore, it can be considered suitable for dealing with these situations (Simar and Wilson 2000).

Table A.1: Peryache and Coelli (2009) endogeneity test.

	test	p-value
2010	3.7336	0.5564
2011	3.7174	0.5542
2012	3.7245	0.5554
2013	3.8782	0.5753
2014	3.7654	0.5610
2015	3.7613	0.5596
2016	5.2353	0.5779

Number of replications=1000, number of inputs=3, number of output=1.
Under H_0 the test statistic is asymptotically distributed according a χ^2 with 4 degrees of freedom.

Appendix B Returns To Scale Tests

This appendix shows the test statistics and the p-values of returns to scale tests applied to the all cross-sections of the panel dataset. We apply the Simar and Wilson (2020) procedure based on randomly splitting the sample into multiple independent subsamples, and comparing the mean of DEA efficiency estimates computed under different returns to scale. Again, we use the library FEAR available for the R software. Compared to the original test proposed by Kneip et al. (2016) this test is not sensitive to the particular random sample-split employed. Given the use of multiple sample-splits, the test employs a bootstrap procedure that exploits the information from the multiple sample-splits and makes results more robust. Table B.1 reports the p-values of the performed tests. For all tests we reject the null hypothesis of constant return to scale at the 0.05 level of significance.

Table B.1: Test for the Returns To Scale of the Production Possibility Sets.

	2010	2011	2012	2013	2014	2015	2016
stat.	4.89	4.55	4.91	4.51	4.88	4.94	4.98
p-value	0.043	0.048	0.042	0.047	0.043	0.041	0.41

Note: Number of splits s=10; number of replications B=1000.

Appendix C Efficiency Indexes

This appendix shows the summary statistics of the the technical efficiency estimates (table C.1) computed in the DEA analysis.

Table C.1: Summary Statistics of Global Malmquist Index by Country and Year

	2010-2011	2011-2012	2012-2013	2013-2014	2014-2015	2015-2016
Belgium	1.023729	0.9914683	1.021071	0.9745408	1.174107	1.176386
Czech Republic	1.58644	1.2459	1.040758	0.9409123	1.06343	1.052881
Finland	1.025678	1.060166	1.03236	0.9109669	0.9655664	1.015481
France	1.272971	1.299812	0.9719953	1.014245	0.8643593	1.334448
Germany	0.9975221	1.009823	1.046858	0.8919319	1.036921	0.9676202
Hungary	1.116017	1.155231	0.8860181	0.8228676	1.051627	1.320907
Italy	1.214269	1.066906	1.360157	0.9798921	1.095637	0.9536903
Netherlands	1.07984	0.8899451	0.6259274	0.6067244	0.6925408	1.843745
Poland	1.817459	1.139448	0.9645223	0.9429906	0.9714354	1.169532
Portugal	0.9609339	1.155502	1.499692	1.223183	0.9439724	0.9641018
Slovakia	2.271597	1.225419	1.018239	0.8728466	1.423647	1.061567
Slovenia	0.9330452	1.018064	1.044809	0.825875	0.7831032	1.034904
Spain	1.344287	1.199313	1.137866	0.8830369	1.085201	1.009918
Sweden	1.009918	1.009918	1.009918	1.009918	1.009918	1.009918
United Kingdom	1.463541	1.463541	1.463541	1.463541	1.463541	1.463541

Appendix D Separability Tests

This appendix shows the p-values of the separability tests applied to all the environmental variables. Again, we use the library FEAR available for the R software. Given the panel structure of the data we perform separability test for each cross-sections between 2010-2016. Moreover, as the performance instability and time execution increase as the number of the environmental variables increases, we apply different separability tests for different sub-samples of environmental variables.

The original test proposed by Daraio et al. (2018) is sensitive to the specific chosen random sample-split. Therefore, following Simar and Wilson (2020), we use multiple sample-splits in order to eliminate much of the sensitivity of the test resulting from the single split. Note that the number of sample-splits should be set as large as is feasible. We use two sample splits, given the computational burden due to the large sample size. The number of bootstrap replications is set equal to 1000 because lower values will likely undermine the performance of the test.

Table D.1 shows the p-values of tests that adopt as null hypothesis that the separability condition holds.

Table D.1: Separability test.

	2010	2011	2012	2013	2014	2015	2016
$Z = \{GDP;\ Retailers\quad Ratio;\ Balance\quad Trade\}$	0.95	0.96	0.97	0.91	0.94	0.97	0.95
$Z = \{EPS;\ Market - EPS;\ ETS\}$	0.92	0.99	0.89	1	0.08	0.56	0.46
$Z = \{Market\quad Structure;\ Public\quad Ownership\}$	0.94	0.43	0.42	0.48	0.37	0.99	0.46
$Z = \{Own.\quad Dispersion;\ Dummy\quad Public\}$	0.34	0.95	0.5	0.96	0.4	0.92	0.97

Note: Number of replications=1000, number of inputs=3, number of output=1, number of splits $s = 2$.
$H_0 : \mathbf{\Psi}_Z^t = T^t$ where $\mathbf{\Psi}^Z$ is the conditional support of $f_{XY|Z}$ and $\mathbf{\Psi}$ is the production possibility set, $t = 2010, ..., 2016$.