The environmental effectiveness of the EU ETS in presence of economic recession and climate policies overlaps

Benoît Chèze[a, b], Julien Chevallier[c] and Emilie Alberola[d]

[a] IFP Energies nouvelles, 1-4 avenue de Bois-Préau, 92852 Rueil-Malmaison, France.
[b] ECONOMIX – CNRS, Paris-Ouest University ; UMR210 Economie Publique, INRA, Climate Economics Chair, Paris, France
[c] LED, Paris 8 University; IPAG Business School (IPAG Lab), 184 Boulevard Saint-Germain, 75006 Paris, France.
[d] I4CE and HEC Paris.

Abstract

We estimate the main drivers of CO_2 emissions for the 1,453 power plants included in the EU ETS using firm-level panel data. During phases I and II, there has been a debate whether the economic crisis was ultimately the only factor behind the fall in CO_2 emissions. We find that CO_2 emissions are effectively impacted by economic activity, in conjunction with renewable energy deployment, and other environmental policies including carbon pricing. We conclude that the EU Commission's flagship climate policy keeps a certain degree of effectiveness but only during the Phase I of the EU ETS – which also corresponds to the period before the recession – which could be enhanced by a better coordination of overlapping climate policies.

JEL Codes: C23; L94; Q48; Q54.

Keywords: European carbon price; Climate policy overlaps; Dynamic Panel data.

.

1. Introduction

Has the European Union Emissions Trading Scheme (EU ETS) effectively reduced CO_2 emissions? The aim of this scheme, which was set up in 2005, is to reduce CO_2 emissions in Europe by setting emissions caps for over 11.000 installations[1] which are required to return a volume of allowances that corresponds to their verified CO_2 emissions for each annual compliance assessment. The EU ETS is in force in 31 countries[2], and covers over 45% of their overall greenhouse gas (GHG) emissions. Phase II lasted from 2008 to 2012.

In fact, the European Commission stated in its report on the operation of the EU ETS in November 2012 that "*the EU ETS is facing a challenge in the form of an increasing allowance surplus, primarily due to the fact that the economic downturn has reduced emissions by more than was expected.*"[3] It is indeed likely that the slowdown in economic activity within the European Union did have an impact on the fall in CO_2 emissions, but can we argue that the downturn was the main reason or even the only reason for that fall?

Besides the 2008 economic recession, the environmental effectiveness of the EU ETS may be endangered by overlapping climate policies. We distinguish two kinds of overlaps. On the one hand, several environmental regulation tools coexist with emissions trading: i) the EU Commission Climate Energy Package, ii) renewable energy deployment objectives and iii) specific sectors regulations. On the other hand, this policy mix is implemented at both the regional and national levels.

Indeed, factors other than the economic crisis could also have played a role, especially the actual efforts made to decarbonize the economy, and increasing renewable energy's share in the energy mix. Indeed, the commitments made at the European level, which resulted in the so-called "20-20-20" targets[4], were implemented via a series of directives, including the directives on renewable energy and energy efficiency, which were combined with national policies. These commitments were reflected by a notable development of renewable energy in most States.[5] In which case, can we estimate to what extent these efforts contributed to reducing CO_2 emissions? Likewise, we need to ask whether changes in the price of energy affected CO_2 emissions or whether the allowance system, and specifically the

[1] The sectors covered are mainly: energy production (which accounts for over 60% of the total emissions concerned by the EU ETS), and the "other combustion" segment, which includes units that are typically used to generate heat in order to support other industrial or urban activities, followed by cement plants, refineries and steel works, which account for roughly the same level of emissions.
[2] The 27 Member States, Croatia, Norway, Liechtenstein and Iceland.
[3] European Commission, Climate Action, http://ec,europa,eu/clima/policies/ets/index_en,htm
[4] Directive 2009/28/EC on renewable energies established a European framework for the promotion of renewable energies, which set binding national renewable energy targets, in order to achieve a 20% share of renewable energy in energy end-consumption by 2020, to reduce CO_2 emissions in European Union countries, and to increase energy efficiency by 20% by 2020.
[5] European Commission, *Renewable Energy Progress Report*, 2013, page 3. http://eur-lex,europa,eu/LexUriServ/LexUriServ,do?uri=COM:2013:0175:FIN:FR:HTML

carbon “price signal” that it reflects, effectively played a role by encouraging fuel-switching in energies and investments in technologies that emit less carbon.

The power sector is also exposed to different kinds of energy or environmental policies that also impact fossil fuel power plant emissions levels. On top of the carbon price that was established in 2005, national policies to develop renewable energy are widespread in the European Union. Since 2009, national targets are consolidated in a directive at the European level and Member States established action plans to reach the desired development in renewable energy[6]. According to them, electricity from renewable sources will reach 33 % of the total final electricity consumption at the European level in 2020, when it was only 15 % in 2005. To reach their objectives, many Member States have put in place deployment policies such as feed-in tariffs or “green” certificates (Ringel, 2006) that were successful in channelling investments in renewable energy production without any connection to the CO_2 price level. Other environmental command and control policies are also applied in the European power sector, like the *Large Combustion Plant Directive* (LCPD) that limits the use of some power plants since 2008 We thus can take advantage of the data provided in the EU Transaction Log on power plants participating in the EU ETS, to evaluate the impact in terms of CO_2 emissions of the carbon price, but other complementary policies that affect emissions levels.

We choose to focus our analysis on the power sector for various reasons. First, it is the largest sector in the EU ETS in terms of CO_2 emissions. Half of allowances were allocated to power or Combined Heat and Power (CHP) plants (see Figure 5 in the Appendix). It differentiated from the other sectors also because since 2005, it is the only industry that as a whole was short in European Union Allowances (EUAs), i.e., its free allocation of EU allowances was lower than the amount of CO_2 it emitted. This has been anticipated by Member States and comes from two main reasons: the perception that cheaper abatement options exist in the power sector than in other industrial sectors, and the low risk of carbon leakage in power production (Ellerman and Buchner, 2008). It has led power producers to include the carbon price in their operating decisions.

From an original database of 1,453 electricity generation plants running on fossil fuel in Europe, the focus of this article is to provide quantitative answers to these questions, based on panel data econometrics for the EU 27. We attempt to link CO_2 emissions with a series of explanatory variables that have an impact on emission trends, and to gauge their relative contributions.

The remainder of the paper is organized as follows. Section 2 presents the literature review. Section 3 details the methodology. Section 4 contains the empirical results. Section 5 concludes.

[6] All national action plan on renewable energy are freely available on the European commission website: http://ec.europa.eu/energy/renewables/action_plan_en.htm

2. Background

Few studies have attempted to evaluate the effects of the EU ETS in terms of emissions reductions. Perhaps among the first in this strand of literature, Ellerman and Buchner (2008) make use of preliminary verified emissions and allowance allocation data to diagnose the extent of "over-allocation" during the 2005-06 period. Anderson and Di Maria (2011) provide another ex-post evaluation of phase I by resorting to dynamic panel data modeling. Based on emissions data from the Community Independent Transactions Log (CITL) and Industrial CO_2 emissions from Eurostat (at the aggregated country level), their analysis hardly establishes that abatement occurred over 2005-2007. This view is shared by most studies which reflect on this trial period of the EU ETS, gearing towards the conclusion that no abatement would be indicated (Ellerman and Buchner, 2007; Convery and Redmond, 2007). Martin et al. (2012a) have further extended this argument to 2008-2012; based on a literature review on aggregated industrial data, the evidence of the effect of the EU ETS on emissions of participating firms is not conclusive.

Firm-level data would provide more insights into the emissions reductions actually achieved under the EU ETS. Abrell et al. (2011) perform such a task by means of robust regression, matching CITL and Amadeus data to determine firm-level performance. Overall, they capture 59 % of the total verified emissions between 2005 and 2008. After controlling for various characteristics of firms' performance, their results imply some degree of emissions abatement during phase II. This rather indirect finding stems from the fact that emissions reductions were not only achieved by reductions in the economic activity of the firms during the sample period. The authors admit, however, a few caveats in their data treatment procedure, and conclude that their results should be interpreted with caution.

Additional works exist based on firm-level data. Zaklan (2013) also resorts to CITL and Amadeus matched data to establish firm-level evidence of inter- and intra-firm transfers of permits during 2005-2007. Jaraite and Kazukauskas (2012) perform a similar analysis based on transactions between EU ETS installations. Bushnell et al. (2013) investigate the effect of the EU ETS on firm profits by using CITL, Orbis and exchange data. Further on this topic, Jong et al. (2013) match CITL and Orbis data to measure the impact of allowance over-allocation on firms' share prices, especially around the April 2006 market crash. Martin et al. (2012b) match CITL and Orbis data as well to study industry relocation during the first years of the EU ETS. Wagner et al. (2013) estimate the impact of phase I and a part of phase II on German manufacturing plants with CITL and AfiD data, and find that emissions had not fallen significantly by 2010. Nevertheless, these latter studies do not directly seek to evaluate emissions abatement achieved within the EU ETS phases I and II.

In parallel, another strand of literature has developed on the optimal policy mix to reduce CO_2 emissions in the power sector. According to Fischer and Newell (2004), technology policies should remain confined to the promotion of research and development, thus rejecting promotion policies by early market deployment. De Jonghe et al. (2009) and Böhringer et al. (2008) show the interdependence of renewable policies and carbon pricing, which leads to the inefficiency of one of them if they are poorly calibrated. Fisher and Peronas (2010) argue that, in the presence of efficient carbon pricing, other policies such as renewable energy support offer no additional environmental benefits, and have to be justified by other market failures. In the presence of uncertainty on the environmental benefits of the future policy, renewable energy subsidies can be justified only by their contribution to the mitigation of CO_2 emissions (Hoel, 2012; Lecuyer and Quirion, 2013).

As for the assessment of CO_2 abatement coming from renewable energy development, Weigt et al. (2012) examine the impact of the development of renewable energy in Germany on the demand for carbon allowances (and therefore on CO_2 emissions). Approximately 10-16% of the fall in CO_2 emissions in the electricity sector between 2005 and 2011 can be explained by the increase in renewable energy's share of the energy mix.

3. Methodology

This section informs us about the database matching procedure, before moving to the exposition of the explanatory variables of CO_2 emissions. Note that the exhaustive list of explanatory variables can be found in Table 7 of the Appendix. The panel data modelling is also outlined.

3.1. Matching

All industrial sites participating in the EU ETS (approx. 12,000 sites in 31 countries) are required to report their CO_2 emissions every year. We have identified the power plants by matching two databases:

- The **European Union Transaction Log** (EUTL)[7] available on the website of the European Commission, with
- The **World Electric Power Plants** (WEPP) database maintained by Platts[8].

The Appendix contains detailed information on the matching procedure. This methodology allows identifying 1,453 accounts in the EUTL between 2005 and 2012 that correspond to power/CHP plants.

[7] Formerly known as the Community Independent Transaction Log (CITL), available at: http://ec.europa.eu/environment/ets/
[8] http://www.platts.com/products/world-electric-power-plants-database

Among these 1,453 power plants, 1,141 were active from 2005 to 2012, 68 retired between 2005 and 2012, and 244 appeared after 2005 either because they were new entrants or because their country integrated the EU ETS. For example, 53 came from the integration of Bulgaria and Romania in the EU ETS in 2007 and Norway in 2008. We include in the sample all this power plants for each year they were in service, i.e., they reported verified emissions.

As a whole, the power and CHP power plants saw a decrease in their CO_2 emissions by 186 Mt during phase 2 (2008-2012), equal to a 14.2% fall from 1,306 Mt in 2007 – the last year of phase 1 – to 1,120 million tonnes (Mt) in 2012. The fall in CO_2 emissions in the power industry would therefore appear to be more circumstantial than structural. Trends in CO_2 emissions were different according to the primary fuel used by the power plant.

After declining sharply in 2008 and 2009, primarily due to the economic downturn, CO_2 emissions from coal-fired power plants actually increased between 2009 and 2012, reaching 846 $MtCO_2$ in 2012. This increase is partly explained by a rebound in coal's competitiveness as a fuel for thermal power plants in Europe, particularly due to the export of the excess coal produced in the United States to Europe, and to the collapse in the carbon price in Europe, which no longer penalized coal-fired power plants in 2011 and 2012.

As displayed in Figure 1, gas and oil-fired power plants experienced the sharpest decline in their CO_2 emissions, which fell by 34% and 30%, respectively, between 2008 and 2012. CO_2 emissions from gas-fired power plants fell from 273 to 175 $MtCO_2$, while emissions from oil-fired power plants fell from 50 to 37 $MtCO_2$.

Insert Figure 1

Additional computational details on the number of installations classified by primary fuel, as well as the average capacity of power generation installations according to primary fuel, can be found in Tables 5 and 6 of the Appendix, respectively.

3.2 Explained Variable: CO_2 emissions of power plants

The CO_2 emissions of power plants constitute the variable of interest in this article.

Insert Figure 2

This variable is pictured as the solid black line in Figure 2. We record a peak in CO2 emissions during the year 2007. This level has subsequently decreased during the years 2008-2009, in line with the economic recession. CO2 emissions in the power sector remain rather stable from 2010 onwards.

More specifically, our aim is to evaluate empirically the relative contribution of the EU ETS (through carbon pricing) on abatement in the European power sector, alongside other factors outlined in the next section.

The academic literature today provides no empirical evaluation of the explanatory factors of CO_2 emissions in the power sector over the period 2005-2012. No ex-post assessment of the contribution of other climate and-energy policies has yet been performed at the scale of the EU. Nevertheless, some studies attempt to evaluate the emissions reductions achieved by the implementation of the EU ETS during the first phase. Ellerman and Buchner (2008) find a reduction in CO_2 emissions between 50 and 100 Mt over 2005-2007. Delarue et al. (2008) evaluate emissions reductions that were between 34 and 88 Mt in 2005, between 19 and 59 Mt in 2006. Feilhauer and Ellerman (2008) estimate that reductions range between 13 and 122 Mt.

3.3 Explanatory Variables: economic, energy and technical factors

Broadly, we are looking to explain the variation of CO_2 emitted by power plants by four kinds of data:

(i) Economic activity

The first data selected to represent the economic activity is the EU-27 GDP calculated by Eurostat, measured as chained volumes in base 100 for the reference year 2005. This variable is reproduced in Figure 2, on the same graph as the dependent variable. The rationale behind the inclusion of GDP unfolds as follows. Economic conditions influence positively the demand of electricity by companies and households, pushing fossil-fuel power plants' production and hence CO_2 emissions up.

This second period between 2008 and 2012 was affected by the 2009 economic downturn, which was characterized by a world-wide economic contraction that began in late 2007 and took a serious turn for the worse in 2008. Against this backdrop, observers have repeatedly argued that the economic downturn, which is synonymous with a contraction in industrial output, was responsible for the recorded decrease in CO_2 emissions in the power sector.

(ii) Energy markets data

Insert Figure 3

The p**rice of primary energy influence**s **the use of respective power stations through their marginal cost** (see Figure 3). To evaluate the impact of production costs in thermal power plants' use, we select coal and gas as the two main fuels used in thermal power plants in Europe. Coal and gas prices are retrieved from Thomson Financial Datastream, using the API 2 CIF ARA Month Ahead contract for coal, and the Zeebrugge spot contract for gas. Annual averages are calculated, and the prices are converted into Euro per MWh.

The CO_2 price in Euro/tCO_2 comes from ICE exchange database. We use the price of the contract for delivery for next December, as it is the most liquid carbon asset traded. Annual average is calculated as the average of all closing prices of the year. The main hypothesis tested regarding the environmental effectiveness of the EU ETS in terms of actual abatement is linked to the level of the carbon price. Indeed, the CO_2 price can, when high enough, incite a switch of production between CO_2 intensive power plants to less emitting ones.

The first period was a learning phase: around 1.2 billion allowances were allocated every year, almost entirely free of charge. As this surplus could not be used in phase 2, the price of phase 1 allowances fell to zero. The second period corresponded to the Kyoto Protocol application phase, where the EU ETS CO_2 emissions reduction targets for each Member State were in line with those defined in the agreement. Allowances were still mostly allocated free of charge. Unlike in phase 1, the option of holding phase 2 allowances over to phase 3 enabled the carbon price to remain at a significant level for a time, before gradually falling to below €4.00 per tonne.

(iii) Technical data of the power plants

Among technical factors, we retain: the primary fuel used by the power plant, the technology of the turbine of the units of the power plant, and the presence of CHP units in the power plant. CHP units have part of their CO_2 emissions that can be attributed to heat production and respond to different economic incentives.

Moreover, we take into account power production from low carbon technologies: nuclear and renewable. As they have typically a lower marginal cost of production than thermal power plants, nuclear, hydro and other renewable electricity are the first ones to respond to the electricity demand. They usually come first in the merit order of production.

Last but not least, we control for the production capacity of the power plant. Large thermal power plants will tend to emit more CO_2 emissions than smaller units. This factor is analyzed jointly with the energy efficiency of the power plant. For a similar level of production, less energy efficient power plants will emit more CO_2. On the other hand, they will tend to be less used than more efficient ones as their use is less profitable.

(iv) Other energy or environmental policies

Power plants that are submitted to use restriction under the Large Combustion Plant directive (20,000 hours between 2008 and 2015) are identified on the European Environmental Agency website. The generation capacity of power plants in MW is the sum of the capacity of all production units in the power plant. It comes directly from the database World electric power plant edited by Platts. We take the year of commissioning of the power plant from the same source as a proxy of energy efficiency of the power plant, assuming older plants are less efficient. Cogeneration plants are identified as a percentage of MW that comes from CHP units. Primary fuel and type of units are modelled as dummies.

We also take into account low carbon power generation. We take the national data from Eurostat in GWh and separate those between hydro, nuclear and fossil fuel generation. Figure 4 shows the relative importance of various types of non-CO_2 emitting forms of generation *vs.* CO_2-emitting generation. For renewable technologies (except Hydroelectricity production), although climatic variations play an important role in the production level of these technologies, the large increase in recent years**Erreur ! Source du renvoi introuvable.** is mostly due to the expansion of the production capacity in Europe, mainly wind farms and solar panels. Hydroelectricity production mainly depends on precipitation variations as production is almost not increasing in Europe. Nuclear production depends mainly on the availability of nuclear reactors that can overcome long periods of outage for maintenance.

Insert Figure 4

Note: we neglect to consider meteorological conditions. In case of extreme weather (i.e., colder than usual in winter or hotter than usual in summer), there is an increase in heating or cooling consumption. Hence, meteorological data also influence CO_2 emissions through the demand for electricity. Nevertheless, weather variations flatten on a yearly average, the timescale of our data. We do not analyse, either, the magnitude of CO_2 emissions off-shoring, as there are limited interconnections with distribution networks of countries outside the EU.

3.4 Econometric specification and estimation methods

Recall that the aim of this article is to identify and quantify the most important determinant of CO2 emissions of the power plants concerned by the EU ETS. To do so, our database allows us to keep track of the verified C02 emissions of the 1,453 electricity generation plants running on fossil fuels in Europe and its potential drivers from 2005 to 2012, *i.e.* from the beginning of the EU ETS to the end

of its second phase. Thus, thanks to this panel-data sample where cross-sectional units correspond to these 1453 plants we are able to estimate at the micro-level the relationship between CO2 emissions of the European power sector and their main drivers. Moreover, our panel-data sample is closer to time series data than to cross-sectional data. It thus appears suitable to include in our empirical model the lag dependent variable among the regressors; yielding to a so–called dynamic panel data model.
Section 3.4.1 presents the econometric specification of our model and Section 3.4.2 explains why the generalised method of moments technique (GMM) is the most appropriate econometric method for the treatment of dynamic panel models with a relatively large number of cross-sections and small observations over time, as is the case here.

3.4.1 A dynamic panel data modelling

We propose the following dynamic panel data model to test for the influence of previously identified CO2 emissions of power plants determinants:

$$ly_{i,t} = \gamma ly_{i,t-1} + X'_{i,t}\beta + \alpha_i + \epsilon_{i,t}\ ,\ \forall\, i,t \tag{1}$$

with $t = \{2005, \cdots, 2012\}$ the period on which CO_2 emissions data have been obtained, *i* corresponds to each of the 1,453 electricity generation plants running on fossil fuels in Europe. Thus specified the dependent variable of our model, $ly_{i,t}$, corresponds to the logarithm of the verified CO_2 emissions (expressed in ton) of the *i-th* power plant at time *t*. $X'_{i,t}$ is the vector of explanatory variables summarized in Table 7 of the Appendix[9]. There are *K* regressors in $X'_{i,t}$ not including a constant term ($X'_{i,t} = \left(x^1_{i,t}, x^2_{i,t}, \ldots, x^k_{i,t}, \ldots, x^K_{i,t}\right) \forall\, i,t$) and, as usual, $(\alpha_{\mathrm{i}} + \epsilon_{\mathrm{i,t}})$ correspond to the composite error term. The heterogeneity, or individual effect is captured by the constants α_i which account for those fixed and inherent factors in each power plant that may be observed or unobserved; all of which are taken to be constant over time *t*. Finally, $\epsilon_{i,t}$ includes effects of a random nature that are not considered in the model. According to Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998), we assume that α_i and $\epsilon_{i,t}$ are independently distributed across *i*, $\epsilon_{i,t}$ is zero mean and $\epsilon_{i,t}$ are independent over *t* and *i* [10].
Because our panel-data sample is closer to time series data than to cross-sectional data; it thus appears suitable to include the lag dependent variable, $ly_{i,t-1}$, among the regressors for studying the determinants of verified CO_2 emissions of the power plants concerned by the EU ETS. This lagged term accounts for the short-term dynamic and for the conditional convergence among installations in relation to their verified emissions. A significant γ coefficient between 0 and 1 would be indicative of this variable's conditional convergence. The larger the coefficient, the greater the effect of the inertia

[9] All variables are expressed in natural logs, unless otherwise specified.
[10] These assumptions would imply moment restrictions that are sufficient to identify and estimate Eq. (1) consistently using a GMM-based approach for *T > 3* (see Arellano and Bond (1991) or Blundell and Bond (1998), among others).

as an explanatory factor of its own evolution, as well as the slower the convergence speed among the installations. With a double log specification and the remaining factors conditioned, the coefficient β_k would reflect the short-term elasticity between the verified CO_2 emissions of the power plants and the $x_{i,t}^k$ variable, while the long run adjustment can be easily deduced by dividing these estimates by $1-\gamma$, *i.e* $\frac{\beta_k}{1-\gamma}$.

3.4.2 Estimation methods

The econometric specifications of Eq. (1) is characterized by a dynamic structure that specifies the dependent variable for an individual ($ly_{i,t}$,) to be partially dependent on its value during previous periods ($ly_{i,t-1}$,). Thus, conventional panel-data estimation approaches, such as the *Within Groups (WG) estimator*, are not appropriate as $ly_{i,t-1}$, is not a strictly exogenous regressor but a weakly exogenous (predetermined) variable. Indeed, the standard techniques used to deal with the unobservable heterogeneity represented by the α_i are not consistent in this specific case as they yield to an endogeneity problem for the following reason. The *WG estimator* eliminates the α_i by mean-differencing for any variable included in model (1). However, the transformed variable of the lag dependent variable (*i.e.* $\widetilde{ly}_{i,t-1} = ly_{i,t-1} - \overline{ly}_{i.-1}$) is still correlated with the transformed error (*i.e.* $\tilde{\epsilon}_{i,t-1} = \epsilon_{i,t-1} - \overline{\epsilon}_{i.-1}$) because $\overline{\epsilon}_{i.-1}$ contains $\epsilon_{i,t-1}$, which is clearly correlated with $ly_{i,t-1}$ by construction (Anderson and Hsiao, 1982; Hsiao, 1986)[11]. To solve this endogeneity problem and to control for the α_i at the same time, one have to first-differencing rather than mean-differencing Eq. (1) to remove the fixed effect. Our generic econometric specification Eq. (1) thus becomes:

$$\Delta ly_{i,t} = \gamma \Delta ly_{i,t-1} + \Delta X_{i,t}'\beta + \Delta\epsilon_{i,t}\ ,\ \forall\ i,t \tag{2}$$

Where $\epsilon_{i,t}$ is now assumed to be serially uncorrelated (this assumption is testable, see below). Consistent estimator can then be obtained by *Instrumental Variables (IV)* estimation of the parameters in the first-difference model (Eq. (2)), using appropriate lags of regressors as the instruments for the transformed variables of the weakly exogenous (predetermined) regressors. This two-step estimation procedure – *i)* first-differencing rather than mean-differencing Eq. (1) and then *ii)* applying a kind of *IV* approach to Eq. (2) – has been proposed by Anderson and Hsiao (1982), Holtz-Eakin et al. (1988), and Arellano and Bond (1991), among others.

Anderson and Hsiao (1982) proposed *IV* estimation using $\Delta ly_{i,t-2}$ or simply $ly_{i,t-2}$ – which is uncorrelated with $+\Delta\epsilon_{i,t}$ as long as the errors are serially uncorrelated – as a valid instrument for

[11] With $\overline{ly}_{i.-1} = \sum_{t=2}^{T} \frac{ly_{i,t-1}}{T-1}$ and $\overline{\epsilon}_{i.-1} = \sum_{t=2}^{T} \frac{\epsilon_{i,t-1}}{T-1}$, respectively.

$\Delta ly_{i,t-1}$ in Eq. (2), for all i and $t \geq 3$[12]. The regressors $X'_{i,t}$ are used as instruments for themselves as they are strictly exogeneous, otherwise, they can also be instrumented. Although this *2SLS* estimator is consistent, it is not asymptotically efficient when the panel has more than three time series observations. Moreover, its inefficiency might be quite large for a small sample.

Holtz-Eakin et al. (1988) and Arellano and Bond (1991) pointed out these inefficiency problems and propose an alternative, more efficient, *GMM-based* approach: the *GMM-DIF* estimator. Using the first difference model (Eq. (2)), the basic idea is to employ the levels of the series lagged two periods or more (*i.e.* $ly_{i,t-s}$ for $s \geq 2$) as instruments in the *GMM* procedure to overcome the problem of $E(\Delta ly_{i,t-1}\Delta\epsilon_{i,t}) \neq 0$. Moreover, *GMM-based* approaches have important advantages over other panel data methods for estimating a dynamic panel data model like (1). First of all, the use of instrumental variables in the *GMM* procedure allows parameters to be estimated consistently in models with endogenous right-hand-side variables (Arellano and Bond, 1991; Blundell and Bond, 1998). Second, estimates will no longer be biased by omitted variables that are constant over time – installation-specific fixed effects (Holtz-Eakin et al., 1988). Third, the use of instruments potentially allows consistent estimation even in the presence of measurement errors (Bond et al., 2001).

The (one-step) Generalized Method of Moments (*GMM*) estimator is also called the Arellano-Bond estimator after Arellano and Bond (1991), who detailed the implementation steps for the estimator and proposed tests on the assumption that $\epsilon_{i,t}$ are serially uncorrelated. This estimator can be considered as an extension of the Anderson-Hsiao estimator. The approach adopted by Arellano and Bond (1991) is based on the notion that the estimator proposed by Anderson and Hsiao (1981) does not fully utilize all information available in the sample. Compared to its predecessor, the *GMM* estimator allows for more efficient use of information in the dataset by introducing additional lags of the dependent variable as an instrument. In offering these additional instrumental variables, the *GMM* estimator proposed by Arellano and Bond (1991) leads to more efficient estimates.

It is well-known, however, that the *GMM-DIF* approach, poses serious bias problems when the series used in the model exhibit significant persistence, as is the case with the variables considered in model (1). This persistence results in weak instruments, meaning that the correlation between the instrument and the variable to be instrumentalized is small, and the *GMM-DIF* estimator would be poorly behaved (this problem is also present in 2SLS).

Arellano and Bover (1995) and an alternative estimator to solve this weak instrument problem, which is the alternative we use in this paper. Specifically, they propose estimating a system of equations (*GMM-SYS*) in both first-differences and levels, where the instruments in the level equations are now lagged first differences of the variables. Most of available instruments for the level equation are mathematically redundant with the instruments used for the difference equations. As a result, only one

[12] If more lags of the dependent variable are included in the model, we have of course to go further back with lags in order to find valid instruments.

first difference lag is used for each period and instrumenting variable. For example, $\Delta ly_{i,2}$ *instruments* $ly_{i,3}$; $\Delta ly_{i,3}$ *instruments* $ly_{i,4}$ and so on. Using Monte Carlo simulations, Blundell and Bond (1998) and Bond et al. (2001) have shown that instruments for the level equations are still informative even for persistent time series. Because of the good performance of the *GMM-SYS* relative to the *GMM-DIF* estimator in terms of finite sample bias and efficiency, it has become the most widely used estimator when estimating dynamic panel data models.

The most widely used tests for validating the assumptions involved in the *GMM* are the *m1* and *m2* tests, which are first and second-order serial correlation tests of the estimated residuals, respectively, and the *Sargan test*, which checks the validity of the instruments used. If the error component $\epsilon_{i,t}$ in Eq. (1) is serially correlated, the *GMM* estimators will not be consistent due to the fact that some of the instruments will be invalid. If it is not serially correlated, there should be evidence of negative first-order serial correlation and no evidence of second-order serial correlation in the first differences of the errors $\Delta\epsilon_{i,t}$. Thus, the value of the statistic *m1* must be negative and its associated *P-value* should be small (less than 0.05, for example), while the *P-value* associated with the $m2$ test should be high (greater than 0.05, for example). The *m1* and *m2* tests are based on the standardized residual covariance matrix and are asymptotically *N(0, 1)*. The null hypothesis of these tests is that $Cov(\Delta\epsilon_{i,t}, \Delta\epsilon_{i,t-s}) = 0$ for $s = 1,2$ is rejected at a level of 0.05 if *P-value* < 0.05. The *Sargan test* is distributed chi-squared (χ^2) with degrees of freedom equal to the number of instruments minus the number of parameters to be estimated under the null hypothesis that the instruments are valid. The Sargan statistic which determines whether the moment conditions selected are valid is used to test the validity of the overidentifying restrictions. The null hypothesis of the *Sargan Test* is '*overidentifying restrictions are valid*'[13]. Thus, the associated *P-value* of the value of the statistic of the *Sargan Test* should be high. The *Sargan test* is less reliable (and used) in cases like ours, since it requires that the errors be independent and identically distributed, an unreasonable assumption in our case. Another drawback of this test is that apart from detecting serial correlation, it can reject the restrictions if the model is misspecified. Imbens et al.(1998) show that the *Sargan test* has poor size properties. Anyway, the results from the *Sargan test* should therefore be interpreted with care.

[13] Properly speaking, the Sargan/Hansen test of overidentifying restrictions and the Difference Sargan test are used with *difference* and *system GMM*, respectively, to test the validity of the additional instrumental variables. The null hypothesis is '*no correlation between the instruments and the errors*'. For system GMM the *Sargan test* can be used to determine the validity of the additional instruments, as well as the *Difference Sargan test* that compares the results from difference and system *GMM*.

In this article, the relationship between the CO_2 emissions of European power plants and their main determinants, as specified in eq(1), is estimated thanks to the *GMM-SYS* estimator. The next section presents estimates of this estimator.

4. Results

Technical power plants' characteristics but also economic and energy market conditions should have an influence on the CO_2 emissions of power plants. But the magnitude of the influence of these CO_2 emissions determinants seems also to depend on the power plant under consideration, which varies widely among the EU ETS. To take into account the heterogeneity of installations, the role played by these variables on the CO_2 emissions of power plants concerned by the EU ETS is estimated using panel-data econometrics. As detailed below, cross-sectional units of the panel-data sample correspond to the 1,453 electricity generation plants running on fossil fuels in Europe.

We start out by presenting the results obtained for the "whole" sample (Section 4.1), which include all types of primary fossil fuels used by power plants included in the database: coal, gas, and oil (and others) power plants. Recall that our database includes variables representing i) technical power plant characteristics and ii) economic and energy market conditions. As technical data are specific to each type of power plant, it is not possible to include this set of variables in the "whole" sample in order to test and quantify their respective influences. In order to capture characteristics of each kind of primary fuel and the type of power plant analyzed, one needs to break the "whole" sample into these respective sub-samples.

The subsequent sections present then results for the "whole" and sub-samples named as follows: "Coal" (Section 4.2), "Gas" (Section 4.3) and "Oil" (Section 4.4) power plants sub-samples. So defined, for the year 2005 the "whole" sample includes 1,453 power plants, the "Coal" power plants one contains 352 power plants, the "Gas" one 671 power plants and the "Oil" one 248 power plants (see Table 6 of the Appendix).

Tables 1 and 2 present the results for the "whole" sample and the "Coal", "Gas", and "Oil" power plants sub-samples respectively. All variables presented in Table 7 of the Appendix have been tested. For each estimate, results are systematically reported after having used the robust variance-covariance matrix estimates (i.e. after using the standard errors adjusted for the *N* clusters representing the number of installations under consideration).

Unless it is indicated regression results are presented in reduced form. These models were chosen by the general-to-specific approach to econometrics modelling. As usual, ***, ** and * respectively indicate 1%, 5%, and 10% significance levels and (robust) standard errors of the coefficient estimates are reported into brackets. In each column, the dash "–" means that the variable under consideration has been first included but finally removed from the reduced form because its coefficient estimate was not statistically significant at the 10% significance level. Regarding model information, *Number of observations* and *Number of groups* indicate, respectively, the number of observations and the corresponding cross-sectional units of the panel-data sample used to perform each regression. In all tables, the number of instruments, the Wald Chi2 (*P-value*), the *m1* and *m2* tests but also the *Sargan test* are reported.

We now turn to the comments of the results obtained for each sample and sub-sample. We focus on the signs and significance of the coefficients estimated.

4.1 All power plants

Table 1 contains the whole sample estimates. Column (1) presents the reduced model for the determinants of CO_2 verified emissions in the power plant sector (*verified_emissions*). The list of candidate explicative variables is detailed in Section 3.3 and in Table 7 of the Appendix.

Insert Table 1

First, we begin with the comments of Column (1) estimates. The dynamic panel data modelling strategy is accurate since the lagged dependent variable (*verified_emissions, t-1*) is statistically significant at the 1% level. As already explained, this lagged term accounts for the short-term dynamic and for the conditional convergence among installations in relation to the verified emissions variable. A significant coefficient between 0 and 1 would be indicative of this variable's conditional convergence. The larger the coefficient, the greater the effect of the inertia as an explanatory factor of its own evolution, as well as the slower the convergence speed among the installations.

The economic activity (*GDP*) is statistically significant at the 1% significance level. It positively influences the variation of CO_2 emissions as indicated by its positive sign. This result is in line with our previous assumption: if GDP increases (decreases), CO_2 emissions increase (decrease) as well. We assess the sensitivity of CO_2 emissions to the slowdown in economic activity within the European Union, as shown in Figure 2 during the year 2008-09.

Coal (*coal_price*) price is also statistically significant at the 1% significance level. Its coefficient is negative: any increase in the price of coal would reduce the incentive to produce from the coal power plants, which tends to decrease CO_2 verified emissions.

The power plant capacity of production (*mw*) is statistically significant at the 1% significance level. Its coefficient estimator is positive. This finding only picks up a size effect, not an energy-intensity one: the bigger the power plant, the more it will emit in terms of CO_2 emissions.

The large combustion plant directive (*lcpd*) percentage is statistically significant at the 1% significance level. Recall that the LCPD captures the percentage of the production capacity submitted to restricted utilization starting from 2008 under the Large Combustion Plant Directive. It negatively influences the variation of CO_2 emission. As anticipated, power plants that have their time of use limited by the LCPD tend to emit less CO_2 than others. We verify that several layers of regulation are able to influence negatively CO_2 emissions.

Other renewable energy such as solar and wind (*production_rnw*) is equally statistically significant at the 10% significance level. It negatively influences the variation of CO_2 emissions. New sources of renewable electricity production reduce emissions. They negatively influence the variation of CO_2 emissions as indicated by the negative sign. This result is in line with our previous assumption: the development of these alternative productions to fossil fuel reduces the residual demand for thermal power plants. As a consequence, the development of renewable energy does have an impact on the reduction of CO_2 emissions in the power sector.

The coal power plants dummy (*coal*) is statistically significant at the 1% significance level. Its coefficient estimator is positive, which means that coal power plants are all other things being equal more emitting than gas. Besides, the oil and other power plants dummies (*oil* and *other*, respectively) are statistically significant. Both coefficients are negative, indicating that oil and other power plants do differentiate themselves from coal and gas plants. All other things being equal, oil and other power plants are less emitting than coal and gas plants. It is consistent with the fact that oil power plants are generally less used than other power plants as a large part of them are used during peak time, only a few hours per year.

Lastly, the carbon price (*CO2_price*) is statistically significant at the 1% level, but with a counter-intuitive positive sign. It seems to indicate that the higher the CO_2 price, the higher the CO_2 emissions implying that the CO_2 market does not provide the right incentives.

Columns (2) and (3) lead us to dig this issue further. Compared to Column (1), they include three additional sets of variables: (*i*) *Dummy_08*, (*ii*) *CO2_price_p1* and *CO2_price_p2*, (*iii*) *GDP_no_crisis* and *GDP_crisis*. These different variables have been added to capture more precisely the respective effects of (a) the policy design change which occurred between the Phase I and Phase II of the EU ETS and (b) the financial crisis in 2008.

In Column (2), we have chosen to include only the dummy (*Dummy_08*) controlling for which period the observations relate to. *Dummy_08* is equal to 1 for the observations starting in 2008, and 0 otherwise. This dummy variable is statistically significant at the 1% level and negative. Actually the variable *Dummy_08* capture two sets of information which arise at the same time: the Phase II of the EU ETS (January 2008) and the burst of the financial crisis (September 2008). So the negative coefficient of *Dummy_08* indicates that CO_2 verified emissions have been effectively reduced after 2008. However, on cannot discriminate between the two events only with the *Dummy_08* variable as it captures both effects. At a first glance, one cannot interpret this result as the proof that the EU ETS has been more environmentally effective in Phase II than in Phase I as the sign of the carbon price (*CO2_price*) remains positive. We do not comment further this column, as the results are qualitatively similar.

To investigate more in-depth this issue, we introduce in Column (3), besides *Dummy_08*, the variables *CO2_price_p1*, *CO2_price_p2*, *GDP_no_crisis* and *GDP_crisis.*
CO2_price_p1 (*CO2_price_p2*) is a cross-product of the *CO2_price* and the dummy *EUETS_phase1* (and *EUETS_phase2*) [14]. Thus, *CO2_price_p1* corresponds to the price of CO2 during Phase I of the EU ETS, whereas *CO2_price_p2* corresponds to the price of CO2 during Phase II of the EU ETS (*CO2_price_p1 + CO2_price_p2 = CO2_price*). Moving from Column (1) and (2) to Column (3), we replace *CO2_price* by both *CO2_price*_p1 and CO2*_price_p2*. This strategy allows capturing potential changes of the effect of the CO_2 market on verified emissions during Phases I and II.
Given the large changes in the economy that happened during the 2008 subprimes crisis, we also have chosen to try to capture whether or not the effect of the economic activity on CO2 emissions has changed before and after the financial crisis. To do so, the *GDP* variable included in Column (1) and (2) is replaced in Column (3) by *GDP_no_crisis* and *GDP_crisis*. *GDP_no_crisis* corresponds to the *GDP* variable for the period 2005 to 2008. *GDP_crisis* corresponds to the GDP variable for the period 2009 to 2012.

Except for the variables *Dummy_08*, *CO2_price_p1* and *CO2_price_p2*, *GDP_no_crisis* and *GDP_crisis*, coefficient estimates are remarkably stable when going from Column (1) and (2) to Column (3) as robustness check. Note, however, that Gas (*gas_price*) becomes statistically significant at the 1% significance level similarly to Coal (*coal_price*). The coefficient estimator for the gas price is positive. It remains negative for coal. This finding is consistent with the following interpretation. An

[14] *EUETS_phase1* equal to one between 2005—2007 and zero otherwise, *EUETS_phase2* equal to one between 2008—2012 and zero otherwise.

increase in the gas price relative to coal results in substituting the use of coal for gas, which actually leads to an increase in carbon emissions.[15]

Regarding *CO2_price_p1* and *CO2_price_p2*, both variables are statistically significant at the 1% level. *CO2_price_p1* has a negative sign whereas *CO2_price_p2* has a positive one, suggesting an alternate influence of the CO2 market on verified emissions between Phases I and II. We may cautiously interpret this result as the proof that if the EU ETS has been effectively efficient during Phase I, it has not been the case during Phase II. Previous literature has documented the occurrence of emissions cuts during 2005-07 that may be attributable to the creation of the EU ETS. We retrieve this result as the negative sign of *CO2_price_p1* indicates that the carbon price during Phase I did have a negative incentive on verified emissions. In this paper, we complement the body of literature by adding that Phase II has been relatively inefficient in terms of emissions reduction, largely due to the economic decline. The positive coefficient of *CO2_price_p2* reflects actually low allowance pricing.

Regarding *GDP_no_crisis* and *GDP_crisis*, both variables are statistically significant and positive.
The coefficient estimate of *GDP_no_crisis* (.34) is lower than that of *GDP_crisis* (.47) indicating that verified emissions have been more impacted by the economic activity (*GDP*) after the burst of the crisis. Therefore, by contrasting the information embedded in the variables *Dummy_08*, *CO2_price_p1* and *CO2_price_p2*, *GDP_no_crisis* and *GDP_crisis* , we infer that the reduction of the CO2 emissions which occurred after 2008 (negative coefficient of *Dummy_08*), came more from the economic crisis than the effectiveness of the CO2 market. Indeed the coefficient of *GDP_no_crisis* and *GDP_crisis* are both positive and stronger for *GDP_crisis* On the contrary, if the coefficient of *CO2_price_p1* is effectively negative, the one of *CO2_price_p2* becomes positive.

Having detailed the significant variables in Table 1, we briefly comment the non-significant variables included in our database. In the whole sample model, variables that were not significant include the geographical location of the power plant, technical data such as cogeneration percentage of the power capacity of the power plant, commission year and, the type of production unit. Regarding the irrelevance of the geographical location of the power plant, from an economic point of view, this result tends to indicate that electricity markets are sufficiently integrated to avoid country-specific distortions. On top of this economic explanation we may add a statistical reason: other explanatory variables - such as GDP, renewable and nuclear production- are also defined at the national level. It is not surprising that technical variables are not statistically significant in the whole sample, as they are

[15] Although the coefficients are not significantly different from zero, the sign of the coefficient estimator for the CO_2 price to switch price ratio is as expected, i.e., negative. An increase in this ratio means an increase in the price of CO_2 and/or a fall in the switch price, which encourages a switch to technologies that emit less carbon, and therefore does in fact reduce CO_2 emissions.

specific to the kind of primary fossil-fuel used by power plants. For example, some types of turbines are specific to a given fuel: gas turbines or combined-cycle are gas-specific.

4.2 Breakdown by coal, gas and oil plants

Owing to differences between power plants according to their primary fuel, it is not possible to include all variables in the "*whole*" sample model. To test other technical data, the "*whole*" sample is thus divided into a coal power plant sub-sample, a gas power plant sub-sample, and an oil power plant sub-sample. Besides, thanks to the fuel data dummy variables (*coal, oil, other*) in Table 1, we have statistically diagnosed that the "whole" sample results can effectively be further investigated by breaking them up according to the type of fuel. These results are further investigated below in Table 2.

Insert Table 2

4.2.1 Coal power plants sample

Table 2 (columns (1) and (2)) contains the results for the sub-sample of coal power plants. Columns (1) and (2) present the same reduced model but for the influence of the *GDP* variable. Notice that in column (1), we tried to capture the effect of the economic activity before and after the financial crise by introducing *GDP_no_crisis* and *GDP_crisis* respectively. However, according to the *P-Value* of the *Wald test* (86.9%, bottom of Table 2, first column) we cannot reject the null hypothesis that both coefficients of *GDP_no_crisis* and *GDP_crisis* respectively are equal. Thus, the influence of the economic activity on the verified emissions of coal power plants has not changed dramatically before and after 2008. This leads us to estimate the reduced model only with the *GDP* variable to capture the influence of the economic activity. These results are presented in Table 2, Column (2).

Compared to the results obtained for the *Whole Sample* (Table 1, column 3), we only comment notable differences specific to coal installations. The variables *verified_emissions, t-1*, *GDP*, *gas_price, coal_price*, *mw* and *lcpd* remain statistically significant and their coefficients remain stable. Variables related to the influence of the CO_2 market (*EUETS_phase2*, *CO2_price_p1* and *CO2_price_p2*) are not significant, implying that the introduction of the EU ETS did not impact the verified emissions of the coal installations. The baseline production technology is therefore coal, which runs on a daily basis for heating and power production. The influence of the CO_2 market on gas and oil installations is detailed afterwards.

4.2.2 Gas power plants sample

Compared to the Coal sub-sample, the variables related to the influence of the CO_2 market (*CO2_price_p1* and *CO2_price_p2*) become significant in the Gas sub-sample model (Table 2, column (3)). The introduction of the EU ETS did have an impact on the verified emissions of the Gas power plant, as depicted by the negative sign of the coefficient of *CO2_price_p1*. The influence of *GDP_no_crisis* and *GDP_crisis* becomes positive and statistically significant (1.16 and 1.31, respectively) with a stronger effect of the economic activity after the 2008 crisis. The same reasoning as for the whole sample estimates holds regarding the relative influence of the economic activity against the CO_2 market effectiveness on verified emissions. Other coefficients remaining stables, we do not comment them further except for technical data newly introduced.

Dummies for the Combined-Cycled Gas Turbine (CCGT) power plants of first (*gt_c*) and second (*cc*) generation are both statistically significant at the 1% level. The interpretation is that these units emit more CO_2 than other types of production units. It can be explained because CCGT units are generally used on a semi-base level, for longer times than other gas units. Indeed, gas turbines (*GT*) emit significantly less than steam turbines, whereas small units using internal combustion (*IC*) do not differ much from steam turbine.

The rest of the reduced model is almost the same as for other sample and sub-samples. The interested reader can notice the stability of the coefficient estimates as a robustness check.

4.2.3 Oil power plants sample

Table 2 (column (4)) contains the results for the sub-sample of oil power plants.

Compared to other sub-samples, the most striking result is the disappearance of the economic activity effect (GDP, but also *GDP_no_crisis* and *GDP_crisis*) on the verified emissions of oil installations. We would explain that because the only place where oil power plants are still commissioned is in the islands (Malta, Cyprus), where they serve as baseload generation.

Similar to coal and gas sub-samples, we do not comment upon the other significant variables, as their influence on verified emissions remains intact.

5. Conclusions

Contrary to the beliefs vehicled by policy makers and previous academic studies, this paper contributes to the environmental economics literature by showing that the EU ETS keeps some degree of effectiveness, despite the presence of economic recession and climate policies overlaps.

Although the European Commission has launched a debate on options for structural reform of the EU ETS to address the growing surplus of emissions allowances that is building up, identifying that the main cause is largely the economic crisis, this paper provides a new analysis of factors behind the CO_2 emissions reductions in the EU ETS.

The CO_2 price emerging from the EU ETS appears effective in our analysis in reducing CO_2 emissions in the power sector, but it is not the only driver. Other environmental regulation also influences CO_2 emissions of power plants as shown in the case of the Large Combustion Plant Directive.

CO_2 emissions abatements in the power sector come as well from the development of renewable energy production, as they reduce the emissions level of individual fossil-fuel power plants. Recall that most of these new renewable production capacities are put in place at a national level in the form of feed-in tariffs or green certificates, without connection to the carbon price.

These results suggest that coordination of energy, climate and other environmental policies has to be thought out carefully. Interaction between policies has to be taken into account. Nowadays, a low carbon price has emerged from the economic crisis that swept away most of the demand for EU allowances. But this weak price signal is also the result of how the Climate and Energy package has been designed in Europe, with a fixed cap for the EU ETS and fixed renewable energy targets. During the period studied, most of the overlapping emissions reduction comes from renewable policies, but other regulations should not be overlooked as shown by the LCP Directive. As illustrated by our estimates, policies fostering energy efficiency tend to reduce energy demand. Their results in terms of CO_2 emissions in the power sector risk making the price of CO_2 redundant.

Overall, our results suggest, based on the European experience until 2012, that more timely adjustment of policies between each other in the face of changing market conditions has to be considered, which can be relevant in the future design of climate and energy policies not only in Europe, but also in other parts of the world.

References

Abrell, J., Ndoye Faye, A., & Zachmann, G. (2011). Assessing the impact of the EU ETS using firm level data. *Bruegel Working Paper #2011/08*, Bruegel, Brussels, Belgium.

Anderson, B., & Di Maria, C. (2011). Abatement and Allocation in the Pilot Phase of the EU ETS. *Environmental and Resource Economics 48*, 83-103.

Anderson, T.W., Hsiao, C. (1981). Estimation of dynamic models with error components. *Journal of the American Statistical Association* 7, 598–606.

Anderson, T., Hsiao, C. (1982). Formulation and estimation of dynamic models using panel data. *Journal of Econometrics* 18, 47–82.

Arellano, M. (2003). *Panel Data Econometrics*. Oxford University Press, Oxford.

Arellano, M., Bond S.R. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies*, 58, 277-297

Arellano, M., Bover O. (1995). Another look at the instrumental variable estimation of error component models. *Journal of Econometrics*, 68, 29-51

Blundell, R., Bond S.R. (1998). Initial conditions of moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87(1), 115-43

Bond, S.R., Hoeffler, A., Temple, J. (2001). GMM estimation of empirical growth models. *Discussion Paper No. 2048, Centre for Economic Policy Research*, London.

Bowsher, C.G. (2002). On testing over identifying restrictions in dynamic panel data models. *Economics Letters* 77 (2), 211–220.

Böhringer, C., Koschel, H., & Moslener, U. (2008). Efficiency losses from overlapping regulation of EU carbon emissions. *Journal of Regulatory Economics* 33, 299–317.

Bushnell, J. B., Chong, H., & Mansur, E. T. (2013). Profiting from Regulation: Evidence from the European Carbon Market. *American Economic Journal: Economic Policy* 5, 78-106

Convery, F. J., & Redmond, L. (2007). Market and price developments in the European Union emissions trading scheme. *Review of Environmental Economics and Policy* 1, 88-111.

De Jonghe, C., Delarue, E., Belmans, R., & D'haeseleer, W. (2009). Interactions between measures for the support of electricity from renewable energy sources and CO_2 mitigation. *Energy Policy* 37, 4743-4752.

Delarue, E., Ellerman, A.D. & D'haeseleer, W.D. (2008), Short-term CO_2 abatement in the European power sector, *Climate Change Economics* 1, 1–21.

Ellerman, A. D., & Buchner, B. K. (2007). The European Union emissions trading scheme: origins, allocation, and early results. *Review of Environmental Economics and Policy* 1, 66-87.

Ellerman, D. & Buchner, B. K. (2008): "Over-Allocation or Abatement? A Preliminary Analysis of the EU ETS Based on the 2005-06 Emissions Data", *Environmental Resource Economics* 41, 267-287.

Feilhauer, S. M. & Ellerman, A. D. (2008), A Top-down and Bottom-up look at Emissions Abatement in Germany in response to the EU ETS, *CEEPR Working Paper # 08-017*, Centre for Energy and Environmental Policy Research, MIT, Boston, MA, USA.

Eurostat, (2014), European power generation database, Energy Statistics Catalogue, European Environment Agency, Copenhagen, Denmark. Available at: http://epp.eurostat.ec.europa.eu/portal/page/portal/statistics/search_database

Fisher, C., & Peronas, L. (2010), Combining policies for renewable energy: Is the whole less than the sum of its parts? *International Review of Environmental and Resource Economics* 4, 51-92.

Fischer, C. & Newell, R. (2004), Environmental and Technology Policies for Climate Change and Renewable Energy, *RFF Working Paper #04-05*, Resources for the Future, Washington, DC, USA.

Hoel, M. (2012), Second-best Climate Policy, *Memorandum #04/2012*, Department of Economics, University of Oslo, Oslo, Norway.

Jaraite, J., & Kazukauskas, A. (2012). Firm Trading Behaviour and Transaction Costs in the European Union's Emission Trading System: An Empirical Assessment. *CERE Working Paper #2012:9*, Center for Environmental and Resource Economics, Umea University, Umea, Sweden.

Holtz-Eakin, D., Newey, W., Rosen, H.S. (1988). Estimating vector autoregressions with panel data. *Econometrica* 56 (6), 1371–1395.

Hsiao, C. (1986). *Analysis of Panel Data*. Cambridge University Press, Cambridge.

Imbens, G.W., Spad, R.H., Johnson, P. (1998). Information theoretic approaches to inference in moment condition models. *Econometrica* 66, 333–357.

Jong, T., Couwenberg, O., & Woerdman, E. (2013). Does the EU ETS Bite? The Impact of Allowance Over-Allocation on Share Prices. *RCAS Working Paper #2013/54*, Robert Schuman Centre for Advanced Studies, Climate Policy Research Unit, European University Institute, Florence, Italy.

Lecuyer O. & Quirion P. (2013), Can uncertainty justify overlapping policy instruments to mitigate emissions? *Ecological Economics* 93, 177-191

Martin, R., Muûls, M., & Wagner, U. (2012a). An evidence review of the EU Emissions Trading System, focussing on effectiveness of the system in driving industrial abatement. *DECC Technical Report*, Department of Energy and Climate Change, London, UK.

Martin, R., Muûls, M., de Preux, L. & Wagner, U. (2012b). Industry Compensation Under Relocation Risk: A Firm-Level Analysis of the EU Emissions Trading Scheme, *NBER Working Paper #19097*, National Bureau of Economic Research, Boston, MA, USA.

Platts, (2014), World Electric Power Plants Database, *Energy Professional Products*, Platts, McGraw Hill Financial, New York, NY, USA. Available at: http://www.platts.com/Products/worldelectricpowerplantsdatabase

Ringel, M. (2006). Fostering the use of renewable energies in the European Union: the race between feed-in tariffs and green certificates. *Renewable Energy* 31, 1-17.

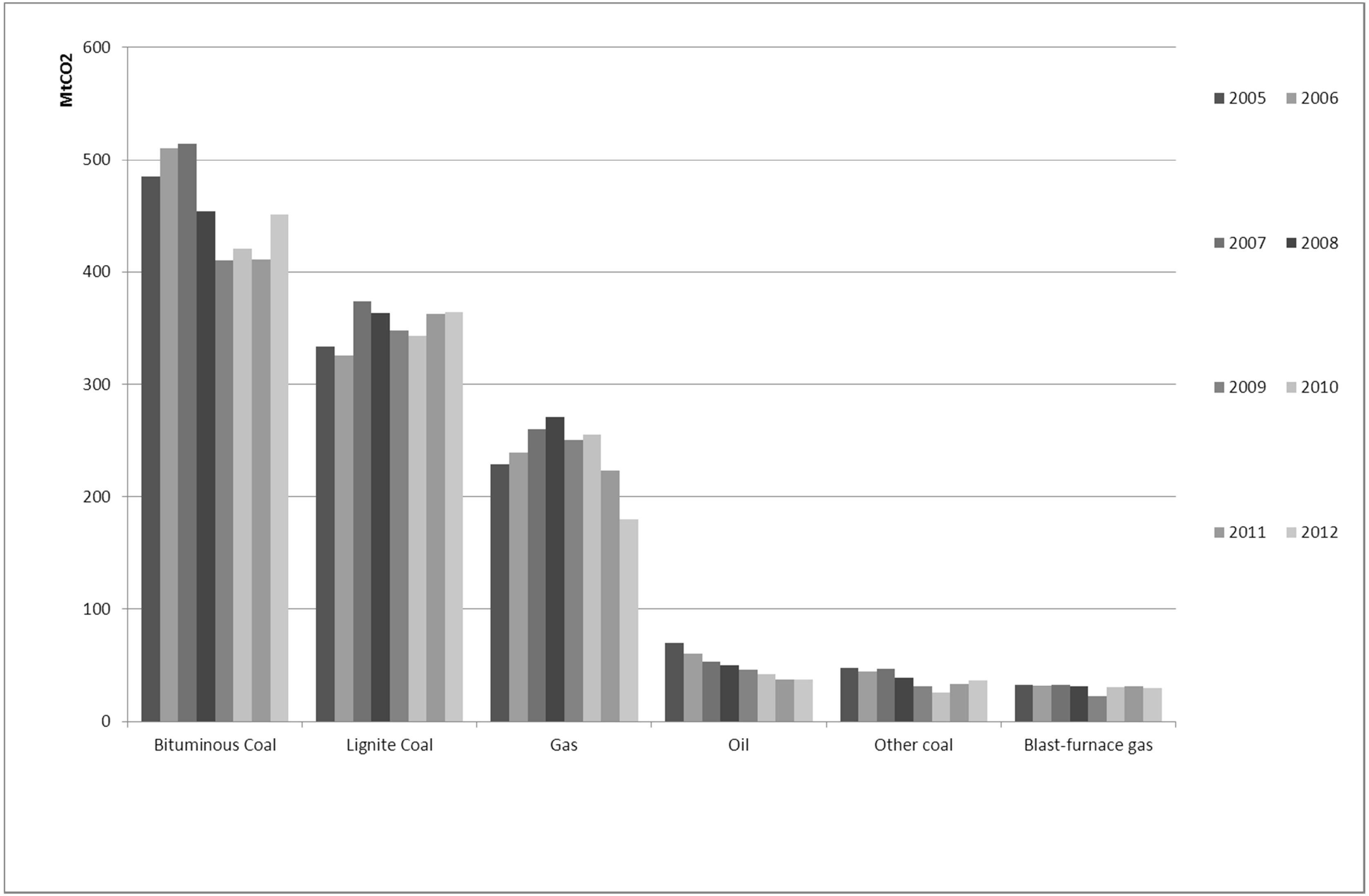
Roodman, D. (2009). A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics* 71 (1), 135–158.

Wagner, U. J., Rehdanz, K., & Petrick, S. (2013). The Impacts of Cap-and-Trade on Industry: Evidence from the European Carbon Market and German Manufacturing Plants. *Working Paper*, University Carlos III Madrid, Madrid, Spain.

Zaklan, A. (2013). Why Do Emitters Trade Carbon Permits? Firm-Level Evidence from the European Emission Trading Scheme. *RCAS Working Paper #2013/19*, Robert Schuman Centre for Advanced Studies, Climate Policy Research Unit, European University Institute, Florence, Italy.

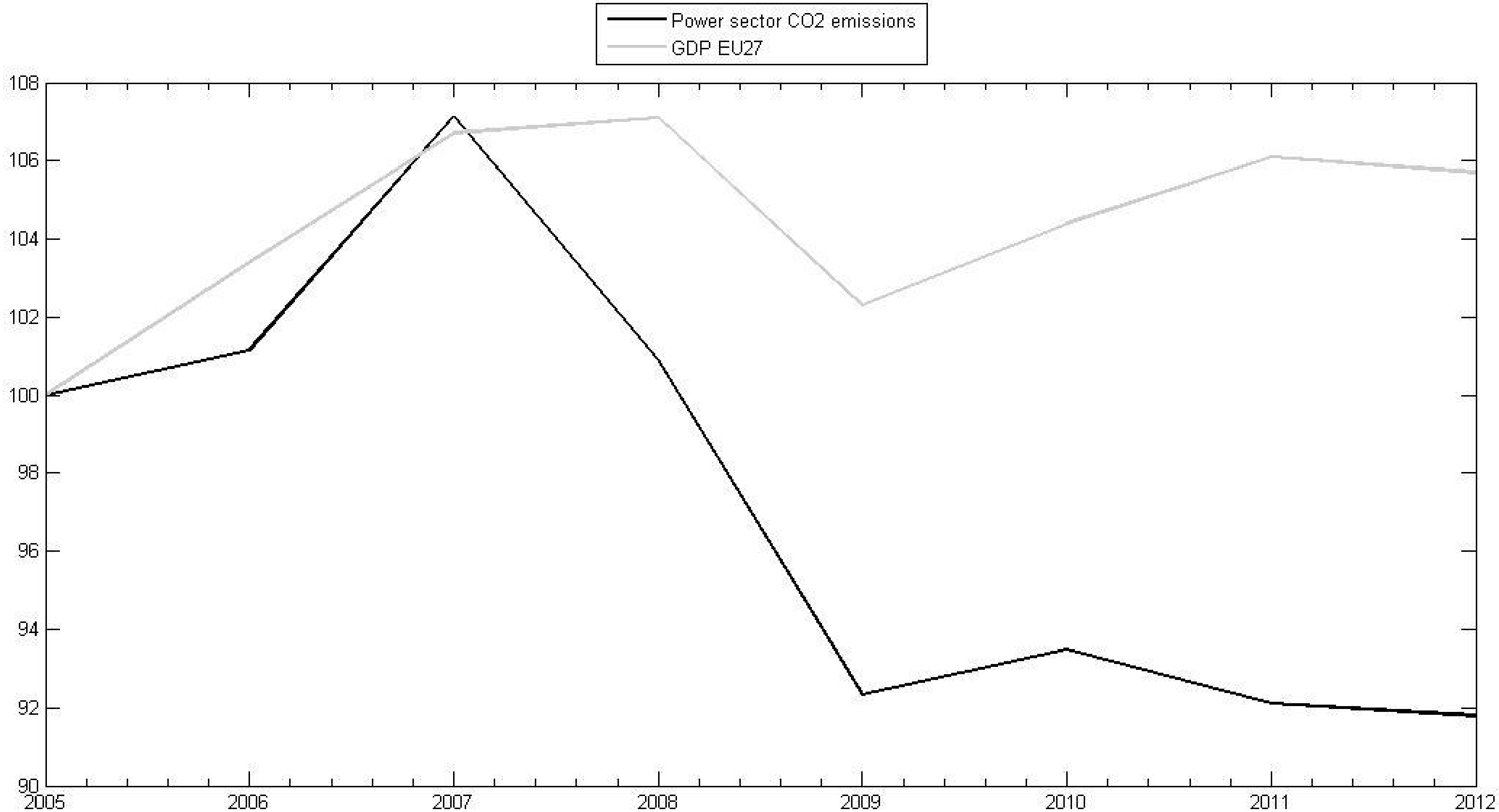
Weigt H., Delarue E. & Ellerman D. (2012), CO_2 Abatement from Renewable Energy Injections in the German Electricity Sector: Does a CO_2 Price Help? *RCAS Working Paper #2012/18*, Robert Schuman Centre for Advanced Studies, Climate Policy Research Unit, European University Institute, Florence, Italy.

Figure 1 -CO_2 emissions for the EU ETS power and CHP generation by primary fuel used (2005-2012)



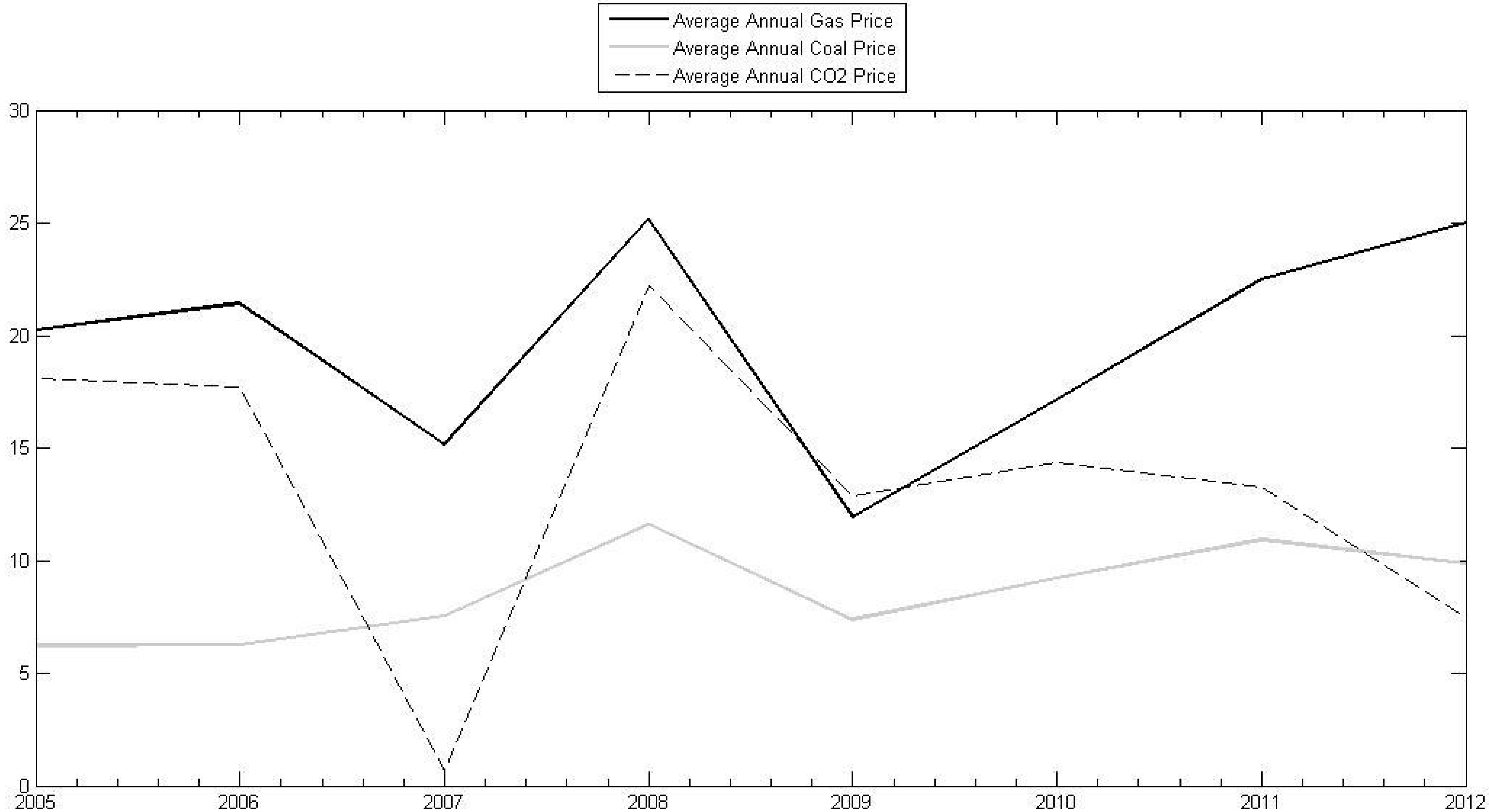
Note: excluding Bulgaria and Romania, as their inclusion in the EU ETS became effective in 2007, the date when they joined the EU. Source: EUTL and World Electric Power Plant (Platts)

Figure 2- Power sector CO_2 emissions vs. GDP EU-27



Source : EUTL, WEPP (Platts) and Eurostat

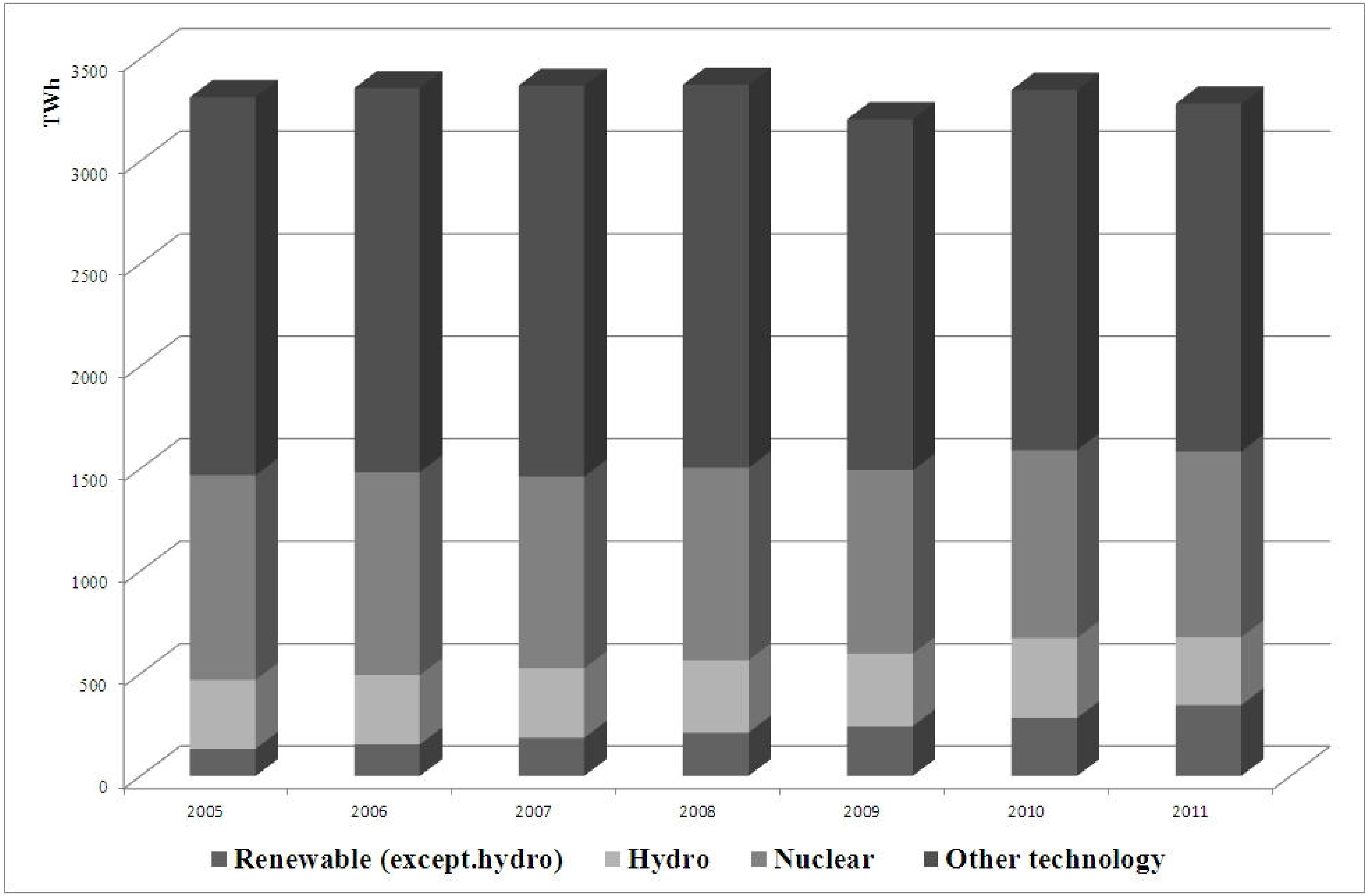
Figure 3 - Energy and CO_2 prices



\

Source : ICE, Reuters

Figure 4 - Electricity production from non-CO_2 emitting sources in Europe vs. Others (fossil-fuel generation)



Source : Eurostat

Table 1 – Regression results for all power plants

	(1) Verified emissions (reduced model)	(2) Verified emissions (reduced model)	(3) Verified emissions (reduced model)
verified_emissions, t-1	.80083907***	.75683247***	.71122178***
	(.0360069)	(.0361244)	(.0372902)
GDP	.39473065**	.4552584**	-
	(.1777183)	(.1911214)	
GDP_no_crisis	-	-	.34403932*
			(.2103423)
GDP_crisis	-	-	.47590122**
			(.2102404)
gas_price	-	-	3.1516219***
			(.5438839)
coal_price	-.36289473***	-.22554544***	-5.723323***
	(.0373817)	(.0546192)	(.9195845)
mw	.18468391***	.22491728***	.26691856***
	(.0341632)	(.0342434)	(.0351803)
lcpd	-.30507906***	-.30493906***	-.32414397***
	(.0919711)	(.0981008)	(.1046296)
production_rnw	-.02075809*	-.02597267**	-.02881748**
	(.0115616)	(.0128423)	(.014479)
coal	.22534633***	.26738018***	.31342866***
	(.041917)	(.0442148)	(.0480763)
oil	-.36803391***	-.43635359***	-.50769996***
	(.0707234)	(.0758195)	(.082377)
other	-.12914634**	-.16143962***	-.1893234***
	(.0555292)	(.0616994)	(.0690424)
CO2_price	.01597551***	.03233932***	-
	(.0058728)	(.0068199)	
CO2_price_p1	-	-	-.64024941***
			(.1099118)
CO2_price_p2	-	-	1.580032***
			(.24078)
Dummy_08	-	-.08507773***	-3.7936191***
		(.029898)	(.586116)
constant	.53436039	.36069233	3.567748***
	(.8552683)	(.9292237)	(1.059993)
Wald Test for			
lgdpnocrise=lgdpcrise *(P-value)*	-	-	25.15 (0.0000)
lco2p1=lco2p2 *(P-value)*	-	-	40.41 (0.0000)
Number of groups	1395	1395	1395
Number of observations	8784	8784	8784
Number of instruments	37	38	41
Wald chi2 (*P-value*)	48042.45 (0.000)	37241.66 (0.000)	29523.67 (0.0000)
m1 (*P-value*)	-7.93 (0.000)	-7.68 (0,000)	-7.35 (0.000)
m2 (*P-value*)	0.54 (0.588)	0.34 (0.735)	0.01 (0.996)
Sargan Test (*P-value*)	525.18 (0.000)	683.49 (0.000)	669.39 (0.000)

Note: the exhaustive list of variables can be found in the Appendix, Table 7.

Table 2 – Regression results: breakdown by coal, gas and oil plants

	(1) COAL Verified emissions (reduced model)	(2) COAL Verified emissions (reduced model)	(3) GAS Verified emissions (reduced model)	(4) OIL Verified emissions (reduced model)
verified_emissions, t-1	.67139435***	.69234029***	.65434606***	.85991686***
	(.0742561)	(.0716609)	(.0610241)	(.0689096)
GDP	-	.52521004*	-	-
		(.2705986)		
GDP_no_crisis	.57562677**	-	1.1643878***	-
	(.2906775)		(.3381774)	
GDP_crisis	.57695465**	-	1.3084343***	-
	(.2877706)		(.3388075)	
gas_price	.15981423***	.16282155***	3.2196435***	2.0393267***
	(.0609958)	(.0502307)	(.6707451)	(.4522675)
coal_price	-.33264639***	-.35877003***	-6.0293986***	-4.2364695***
	(.0739406)	(.0763277)	(1.132703)	(.8565246)
mw	.34716245***	.32587294***	.22837975***	.11839226*
	(.074164)	(.0715961)	(.0452108)	(.0737639)
lcpd	-.31164825***	-.29740712***	-	-
	(.0861578)	(.0849713)		
production_rnw	-	-	-	-.04556662*
				(.0253954)
CO2_price	-	-	-	-
CO2_price_p1	-	-	-.66248286***	-.44865481***
			(.1358119)	(.094548)
CO2_price_p2	-	-	1.8723493***	.62763891***
			(.2868971)	(.1529508)
Dummy_08	-	-	-4.5707394***	-.96878206***
			(.6969218)	(.2910226)
constant	.09394077	.21203186	.7365205	3.9528182***
	(1.085174)	(1.039653)	(1.573493)	(.794099)
gt			-.22576962**	-.06001879
			(.1069662)	(.1795329)
ic			-.15211205	.26814479***
			(.1012102)	(.0831998)
cc			.35608792***	-
			(.0762079)	
gt_c			.22472587***	-
			(.0671805)	
Wald Test for				
lgdpnocrise=lgdpcrise *(P-value)*	0.03 (0.8688)	-	20.26 (0.0000)	-
lco2p1=lco2p2 *(P-value)*	-	-	36.38 (0.0000)	20.16 (0.0000)
Number of groups	349	349	652	248
Number of observations	2300	2300	4084	1587
Number of instruments	34	33	40	37
Wald chi2 (*P-value*)	4450.94 (0.000)	4848.05 (0.000)	10917.05 (0.0000)	6211.04 (0.0000)
m1 (*P-value*)	-3.38 (0.001)	-3.41 (0,001)	-3.82 (0.000)	-4.85 (0.000)
m2 (*P-value*)	-0.26 (0.795)	-0.21 (0.833)	-0.99 (0.322)	1.25 (0.210)
Sargan Test (*P-value*)	317.45 (0.000)	251.82 (0.000)	515.49 (0.000)	143.56 (0.000)

Note: the exhaustive list of variables can be found in the Appendix, Table 7.

Appendix

Matching

The power plants included in the EU ETS were identified using the following two databases:

- the **European Union Transaction Log (EUTL)**, formerly the Community Independent Transaction Log (CITL), which lists the CO_2 allocation and emission levels for EU ETS operators. These data enable an installation to be identified on the basis of various characteristics (e.g. name of the installation, account holder, region, etc.).

- the **World Electric Power Plants (WEPP)**, edited by Platts, which sets out the technical specifications for power generation units. The database specifically documents the technology used by each unit, its theoretical capacity, the primary fuel used, and the year when it was first commissioned. It also contains information on the type of operators, i.e. whether they generate power for their own use, or as a private / public service company.

The article focuses on the EU ETS installations that primarily supply the power that they generate to the electrical grid, and covers 1,453 installations. Sites owned by autoproducers, and those owned by a private company outside the energy industry, i.e. that are not included in the "power generators" or "energy brokers" categories in the WEPP database, are excluded from the research. Conversely, all public service companies are included in the sample.

The linkage of a CITL operator account with the corresponding power generation units in the WEPP database is performed based on three criteria which are found in both databases[16]:

1. the name of the site,
2. the name of the company that owns the site, and
3. the city where the installation is located.

If the three criteria correspond, the accounts are linked. If the name of the company does not correspond, an internet search has been performed in order to identify a potential change of owner. In the event that this difference could be explained, the accounts are linked. The owner company selected is the one recorded in the WEPP database.

[16] The CITL database does not include explicitly the name of the company. However the companies can be identified during Phase 1 of the EU ETS, based on Internet contact addresses. In some cases, the name of the company appears in the account name for sites that were added in Phase 2.

The unit or units recorded as being operational in the WEPP database are then linked to the CITL emissions data. In the event of multiple units on one site:
- The installed capacities of different units are added together;
- The commission year is weighted according to the generation capacity of each unit;
- In the event of different primary fuels on the same site, the fuel selected is the one used by most of the generation capacity;

CHP plants are identified based on the type of unit provided by the WEPP database. A site is considered as a CHP site if over 90% of its generation capacity corresponds to CHP units.

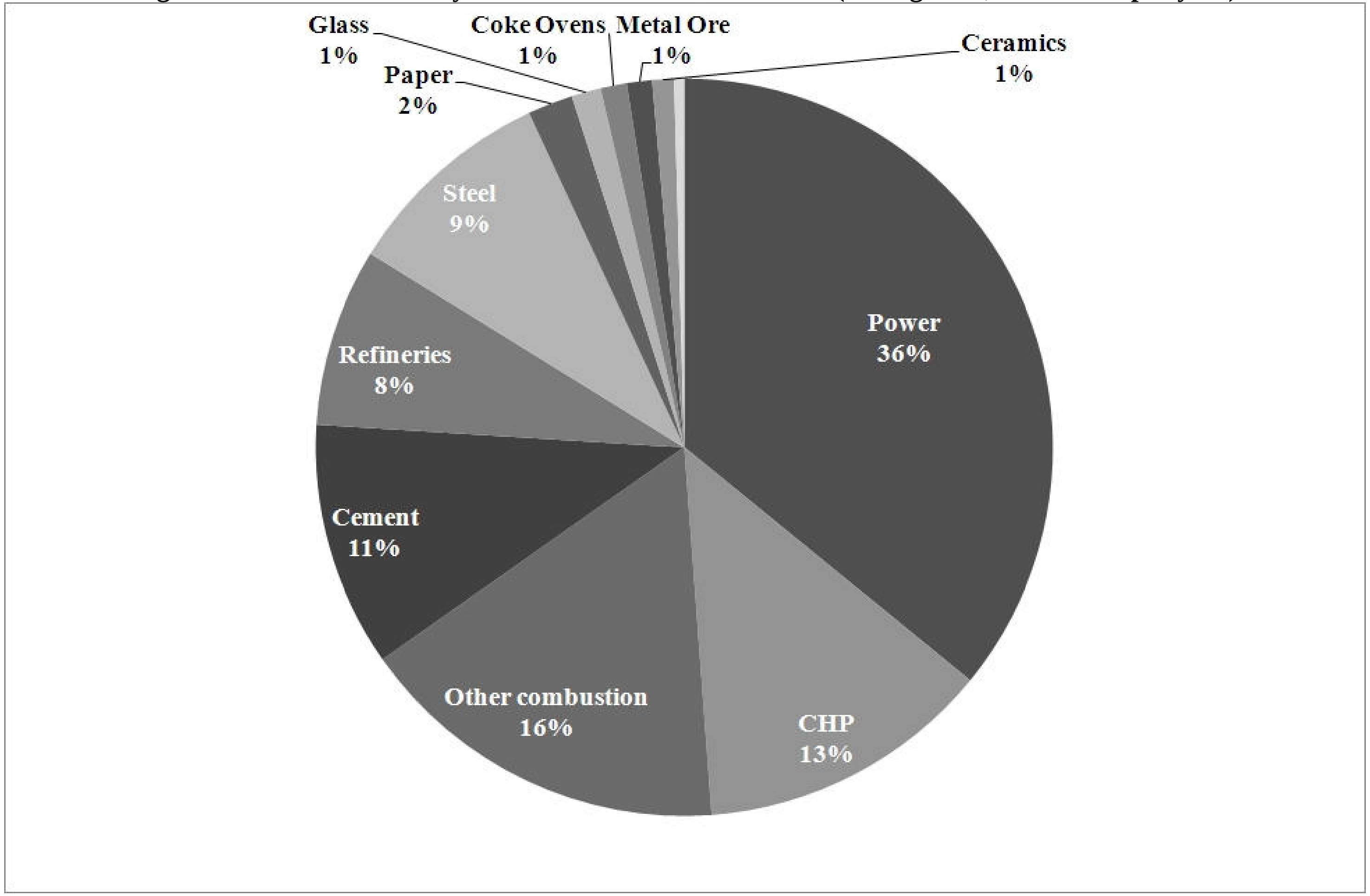
Occasionally, a site in the WEPP database corresponds to several accounts in the CITL. In this case, the generation units are divided based on the information included in the account name or in the National Allocation Plan. In eight cases, we notice either a change of account, or one account is being used to receive allocations while the other is being used to return them. Both accounts have therefore been merged. Lastly, we could not identify the units in three cases. Owing to their low weight in the overall level of verified emissions, these various accounts have been merged into a single account.

Softwares

Database matching is performed under Microsoft Access. Panel data estimates are performed with Stata software.

Figures

Figure 5 – Free allocation by sectors between 2008 and 2012 (average of 1,999 $MtCO_2$ per year)



Source: EUTL and World Electric Power Plant (Platts)

Tables

Table 5 – CO_2 emissions from power and CHP plants by primary fuel in Europe

In $MtCO_2$	**PHASE I**				**PHASE II**			
Primary fuel	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
Power	**922**	**928**	**983**	**923**	**833**	**835**	**826**	**830**
Bituminous Coal	373.8	391.5	392.2	345.4	307.6	311.3	306.6	351.3
Lignite Coal	199.9	194.3	231.6	221.5	211.6	207.2	225.2	225.8
Other Coal	43.6	39.9	41.3	33.3	26.1	20.4	29.0	32.4
Gas	202.9	211.4	228.5	240.0	218.9	221.9	194.0	152.6
Oil	64.7	55.8	48.7	46.0	41.9	37.6	33.5	33.6
Blast-furnace gas	23.6	22.6	24.2	22.6	14.7	20.8	21.9	20.2
Oil Shale	10.0	9.2	12.1	10.3	8.3	12.2	12.1	10.9
Peat	2.7	3.1	3.3	3.4	3.3	3.2	2.9	3.0
Combined Heat and Power	**297**	**305**	**323**	**307**	**294**	**306**	**298**	**289**
Bituminous Coal	111.4	118.6	121.8	108.7	102.7	109.3	104.4	99.5
Lignite Coal	133.7	131.5	142.4	142.0	136.6	136.1	138.2	138.8
Other Coal	4.3	4.4	5.7	5.4	4.7	5.0	4.3	4.2
Gas	26.1	28.3	31.6	31.1	31.2	33.0	29.7	27.4
Oil	5.0	4.1	4.5	4.3	4.4	4.3	3.8	3.9
Blast-furnace gas	9.1	8.9	8.3	8.1	7.1	9.4	9.4	8.9
Oil Shale	0.7	0.7	0.8	0.7	0.7	0.7	0.9	0.9
Peat	3.7	4.7	4.5	4.1	3.8	4.8	4.1	3.3
Total Power/CHP	**1 219**	**1 233**	**1 306**	**1 230**	**1 127**	**1 141**	**1 124**	**1 120**

Source: EUTL, WEPP (Platts)

Table 6 – Number of installations by primary fuel in Europe

Primary fuel used by the installation	2005	2007	2012	2007-2012 Change	% of CHP installations in 2012
Natural gas	671	587	653	66	42 %
Coal (total)	352	342	336	-6	45 %
- ***bituminous coal***	223	217	210	-7	42 %
- ***lignite coal***	87	83	86	3	50 %
- ***other coal***	42	42	40	-2	45%
Oil	248	232	227	-5	12%
Peat	22	20	21	1	71%
Bituminous shale	7	6	6	0	67%
Blast furnace gas	14	11	13	2	46%
Other (total)	139	83	129	46	60%
- ***biomass***	76	60	75	15	81%
- ***solar power***	27	0	27	27	0%
- ***waste***	11	7	10	3	100%
- ***methane***	6	6	4	-2	50%
- ***unknown***	19	10	13	3	31%
TOTAL	**1,453**	**1,281**	**1,385**	**104**	**40%**

Source: EUTL, WEPP (Platts)

Table 7 - Variables in the database

Description	Variable	Type	Unit	Source
General data				
Year	year	Quantitative	Year	EUTL
Identification of the power plant	installationnumber	Quantitative		EUTL
If the emitting power plant has not retired or entered the EU ETS between 2005 and 2012	permanent_A	Binary (=1 if 'true'; 0 else)		EUTL
Emissions and restitution under EU ETS data				
Free allocation of EUAs to the power plant	allowancedistributed	Quantitative	tCO2	EUTL
Surrendered EUAs for compliance by the power plant	surrenderedallowances	Quantitative	tCO2	EUTL
Surrendered CERs for compliance by the power plant	surrenderedcers	Quantitative	tCO2	EUTL
Surrendered ERUs for compliance by the power plant	surrenderederus	Quantitative	tCO2	EUTL
Sum of surrendered EUAs, CERs and ERUs by rhe power plant	totalofallowancessurrendered	Quantitative	tCO2	EUTL
Verified emissions of the power plant	verifiedemissions	Quantitative	tCO2	EUTL
Technical data				
Technical maximum production capacity of the power plant	mw	Quantitative	Mw	WEPP(Platts)
Commission year of the power plant	com_year	Quantitative	Year	WEPP(Platts)
% of the production capacity coming from combined heat and power units	cogen_perc	Quantitative	% of Mw	WEPP(Platts)
% of the production capacity coming from supercritical units	supercritical_perc	Quantitative	% of Mw	WEPP(Platts)
% of the production capacity submitted to restricted utilization starting from 2008 under the LCPD	lcpd	Quantitative	% of Mw	EEA
Fuel data				
Gas power plant using gas as primary fuel	gas	Binary (=1 if 'true'; 0 else)		WEPP(Platts)
Gas power plant using coal as primary fuel	coal	Binary (=1 if 'true'; 0 else)		WEPP(Platts)
Gas power plant using lignite coal as primary fuel	coal_lignite	Binary (=1 if 'true'; 0 else)		WEPP(Platts)
Gas power plant using bituminous coal as primary fuel	coal_bituminous	Binary (=1 if 'true'; 0 else)		WEPP(Platts)
Gas power plant using undifined coal as primary fuel	coal_undifined	Binary (=1 if 'true'; 0 else)		WEPP(Platts)
Gas power plant using oil as primary fuel	oil	Binary (=1 if 'true'; 0 else)		WEPP(Platts)

Gas power plant using peat as primary fuel	peat	Binary (=1 if 'true'; 0 else)		WEPP(Platts)
Gas power plant using blast-furnace gas as primary fuel	bfg	Binary (=1 if 'true'; 0 else)		WEPP(Platts)
Type of production unit				
Combined-cycle gas turbine powerplant	cc_gt_c	Binary (=1 if 'true'; 0 else)		WEPP(Platts)
2nd generation Combined-cycle gas turbine powerplant	cc	Binary (=1 if 'true'; 0 else)		WEPP(Platts)
1st generation Combined-cycle gas turbine powerplant	gt_c	Binary (=1 if 'true'; 0 else)		WEPP(Platts)
Gas turbine	gt	Binary (=1 if 'true'; 0 else)		WEPP(Platts)
Internal combustion engine	ic	Binary (=1 if 'true'; 0 else)		WEPP(Platts)
Steam Turbine	st	Binary (=1 if 'true'; 0 else)		WEPP(Platts)
Activity/Energy data				
Electric renewable gross production in the country (except. Hydro)	production_rnw	Quantitative	GWh	Eurostat
Hydro gross production in the country	production_hydro	Quantitative	GWh	Eurostat
Nuclear gross electric production in the country	production_nuke	Quantitative	GWh	Eurostat
Gross electricity production in the country	production_elec	Quantitative	GWh	Eurostat
Final electricity consumption in the country	elec_final_consumption	Quantitative	GWh	Eurostat
GDP Euro Area	gdp			Eurostat
Price data				
Average annual Zeebrugge gas month ahead price	gas_moy		€/Mwh	Reuters
Average annual API 2 coal month ahead price	coal_moy		€/Mwh	Reuters
Average annual EUA next december price	co2_moy		€/tCO2	ICE exchange
Theoretical switching price of CO2	switch_moy		€/tCO2	Reuters, ICE exchange
Geographical localisation of the power plant				
Austria	At	Binary (=1 if 'true'; 0 else)		EUTL
Belgium	Be	Binary (=1 if 'true'; 0 else)		EUTL
Bulgaria	Bg	Binary (=1 if 'true'; 0 else)		EUTL
Cyprus	Cy	Binary (=1 if 'true'; 0 else)		EUTL
Czech Republic	Cz	Binary (=1 if 'true'; 0 else)		EUTL
Deutschland	De	Binary (=1 if 'true'; 0 else)		EUTL
Denmark	Dk	Binary (=1 if 'true'; 0 else)		EUTL

Estonia	Ee	Binary (=1 if 'true'; 0 else)		EUTL
Spain	Es	Binary (=1 if 'true'; 0 else)		EUTL
Finland	Fi	Binary (=1 if 'true'; 0 else)		EUTL
France	Fr	Binary (=1 if 'true'; 0 else)		EUTL
United Kingdom	Gb	Binary (=1 if 'true'; 0 else)		EUTL
Greece	Gr	Binary (=1 if 'true'; 0 else)		EUTL
Hungary	Hu	Binary (=1 if 'true'; 0 else)		EUTL
Ireland	Ie	Binary (=1 if 'true'; 0 else)		EUTL
Italy	It	Binary (=1 if 'true'; 0 else)		EUTL
Lituania	Lt	Binary (=1 if 'true'; 0 else)		EUTL
Luxembourg	Lu	Binary (=1 if 'true'; 0 else)		EUTL
Latvia	Lv	Binary (=1 if 'true'; 0 else)		EUTL
Malta	Mt	Binary (=1 if 'true'; 0 else)		EUTL
Netherlands	Nl	Binary (=1 if 'true'; 0 else)		EUTL
Norway	No	Binary (=1 if 'true'; 0 else)		EUTL
Poland	Pl	Binary (=1 if 'true'; 0 else)		EUTL
Portugal	Pt	Binary (=1 if 'true'; 0 else)		EUTL
Romania	Ro	Binary (=1 if 'true'; 0 else)		EUTL
Sweden	Se	Binary (=1 if 'true'; 0 else)		EUTL
Slovenia	Si	Binary (=1 if 'true'; 0 else)		EUTL
Slovakia	Sk	Binary (=1 if 'true'; 0 else)		EUTL