Instituto de Engenharia de Sistemas e Computadores de Coimbra

Institute of Systems Engineering and Computers

INESC - Coimbra

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No. 8 2014

ISSN: 1645-2631

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www.inescc.pt

Emissions Trading System and its effects on Electricity Prices

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Abstract

The EU emissions trading system (EU ETS) is a cornerstone of the European Union's policy to combat climate change and its key tool for reducing industrial greenhouse gas emissions cost-effectively. The purpose of the present work is to evaluate the influence of CO_2 opportunity cost on the Spanish wholesale electricity price. Our sample matches Phase II of the EU ETS. A vector error correction model (VECM) is applied to estimate not only long-run equilibrium relations, but also short-run interactions between the electricity price and the fuel (natural gas and coal) and carbon prices. Daily spot prices serve as main inputs of the econometric approach, while the four commodities prices are modeled as joint endogenous variables. Likewise, we include a set of exogenous variables in order to account for the electricity demand conditions and the electricity generation mix. We estimated the dynamic pass-through of carbon price into electricity price. The results show evidence that power producers have been passed on the opportunity cost of freely allocated emission allowances to electricity price, enabling power companies to get windfall profits. The results also confirm significant differences in the pass-through rate of CO_2 emissions costs according to the electricity demand level (peakload vs. off-peakload). Finally we conducted an impulse response analysis to account for the complex interactions between all endogenous variables and to estimate the response of electricity price to shocks in the fuel and carbon prices.

JEL codes: Q58, H23, Q48, C32, L94

Keywords: Environmental policy; Carbon emissions; Electricity prices; Windfall profits; Cointegration; Vector Error Correction Model.

1. Introduction

The EU emissions trading system (EU ETS) is the first international system for trading greenhouse gas emission allowances. The EU ETS works on the 'cap and trade' principle: a limit is set on the total amount of certain greenhouse gases that can be emitted by the factories, power plants and other installations in the system. Transactions of such allocated allowances are then made possible through an EU emissions allowances (EUA) market that provides a price for the CO_2. The cap is reduced over time so that total emissions fall. In 2020, emissions from sectors covered by the EU ETS are expected, by the European Commission to be 21% lower than in 2005. Launched in 2005, the EU ETS is now in its third phase, running from 2013 to 2020. A major revision approved in 2009 in order to strengthen the system means the third phase is significantly different from phases one and two and is based on rules which are far more harmonized than before. This paper builds on previous work by the authors for the Portuguese Electricity Market (Freitas and Silva, 2013, 2012), the complementary division of Iberian Electricity Market (MIBEL). According to our knowledge, we believe this study is an innovative contribution for the state of the art (empirical research in measuring pass-through of CO_2 costs into commodities or products prices) as regards the treatment given to the exogenous variables that aim to reflect the marginal power production unit present in the electricity system. This paper is structured as follows. Section 2 presents a brief literature review. Section 3 describes the functioning of the Spanish electricity market. Section 4 presents the data set. Section 5 describes the methodological approach. Section 6 presents the empirical findings. Section 7 concludes.

2. Literature Review

Previous authors began to assess the interaction between carbon prices and electricity prices. A more extensive literature review regarding the EU ETS impact in the European power sector can be found in Freitas and Silva (2013). Most published analyses conducted in order to estimate the pass-through rate (PRT) of CO_2 cost into electricity prices have not considered the mutual interactions between electricity price, fuel prices (natural gas, coal, fuel, oil) and carbon prices. One of the first studies taking into account those interdependencies was provided by Fezzi and Bunn (2009) where the authors, using multivariate analysis, modeled the prices of all variables as a joint system. Developing a vector error correction model (VECM), with the electricity, gas and carbon prices as endogenous variables, and temperature as an exogenous regressor, the authors estimated the dynamic pass-through of CO_2 price into electricity price for Germany and UK. Other studies have been following that econometric approach, where this article also belongs. Honkatukia et al. (2006) developed a similar model for the NordPool market considering the electricity, gas, coal and carbon prices as endogenous variables. Fell (2010), also for the NordPool and with the same prices variables, added to the VECM the temperature and the reservoir water level as exogenous regressor. Chemarin et al. (2008) estimated with a VECM for the France power market considering the electricity, gas, oil and carbon as prices as endogenous and two different weather variables: the temperature, affecting the demand side of electricity market, and rainfall influencing the electricity production of a country concerning its energy mix. Mohammadi (2009) analyzes the relation between the electricity prices and coal, natural gas and crude oil prices for the USA market. Also for the USA market, Mjelde and Bessler (2009) added the uranium price to the analysis and controlled the weather effects considering temperature variables similar to those used in our model. Thoenes (2011) analyzes the relationship between electricity, fuels and carbon prices for the German market. Using a different methodology, Ferkingstad et al. (2011) studied the Northern European electricity market case and Moutinho et al. (2011) focused on the same market as our study, the Spanish power market.

3. Spanish Electricity Market Background

The Spanish energy sector was liberalized in the late 1990s and the Spanish electricity wholesale market was established in 1998. An important reform implemented in the Iberian wholesale electricity markets was the launch of MIBEL in July 2007.The joint Portuguese-Spanish electricity market allows participants to trade power on either side of these countries' border. The daily spot market (the drive of the current study) is managed by OMEL (Operator responsible for the Electricity Spot Market). The wholesale electricity spot price formation in OMEL uses "market splitting" procedure to solve cross-border congestion management - one single Iberian price if there is no congestion in the interconnection between Spain and Portugal and with distinct prices if there is congestion in the interconnection between both countries (Silva and Soares, 2008). Table 1 shows the total installed capacity and production by technology at the end of 2010. Five firms have been operating in the Spanish power generation market as competitors: Endesa, Iberdrola, Unión Fenosa, Hidroelectrica del Cantábrico and Electra del Viesgo.

Table 1. Electricity Production and Generation Capacity by Technology

	Installed Capacity (MW)		**Electricity Production (GWh)**	
Thermal Fuel/gas	2.860	2,9%	1.825	0,7%
Thermal Coal	11.380	11,5%	22.097	7,9%
CCGT (Natural Gas)	25.235	25,5%	64.604	23,1%
Hydroelectric	17.561	17,7%	38.653	13,8%
Nuclear	7.777	7,9%	61.990	22,1%
Renewables	27.238	27,5%	61.866	22,1%
Others	6.992	7,1%	29.036	10,4%
Total	99.043	100,0%	280.071	100,0%

Source: REE – Red Eléctrica de España: "El Sistema Eléctrico Español". CCGT – combined cycle gas turbine.

The influence of carbon on the price of electricity may not be constant across time. Even the unlikely event of full pass-through of CO_2 costs, the CO_2 emissions associated with electricity generation will remain a function of the generation fuel expended. This in turn induces the increase in the marginal cost of electricity generation due to CO_2 market dependency upon the technology adopted in generation. Assuming that Spanish electricity market is competitive with electricity pricing based on the cost of marginal generator, the changes in electricity prices due to carbon emission prices will depend on the generation technology of the marginal producer. If the electricity market in question has generation technologies at the margin that vary over time, such as the Spanish electricity system, then the electricity price response to carbon price changes will be variable across time. This presents an additional challenge to the estimation of the electricity responsiveness to CO_2 price changes. In order to overcome this difficulty, we included a set of variables in the econometric model which we hope to serve as a proxy of the marginal producer - electricity generated by technology, bided/matched over 95% of the marginal price. Climate variables, such as temperature, rainfall or brightness may also influence the relationship between electricity and carbon prices (Engle et al., 1986).

The basic assumption in our econometric analysis is that changes in electricity prices can be explained by variations in fuel and carbon costs of the price-setting technology. Hence, it is assumed that other costs (capital, operational or maintenance costs) are constant, and that the market structure did not vary over the period of the study. Therefore, changes in prices cannot be attributed to changes in technology, market power, generation capacity or other factors.

4. Data

The present work focuses on Phase II of the EU ETS, ranging from January 01, 2008 to December 31, 2011. Daily data for working days are used (weekend and national holidays are excluded because of significant distinct demand). The electricity series from OMEL is the day-ahead price (€/MWh) for the three load regimes: peakload, off-peakload and baseload. The peak price is the hourly average of spot prices quoted from 8:00h to 20:00h, while the off-peak block covers the remaining time. The base load price is the average of the 24 hourly prices quoted during a day. The natural gas price (€/MWh gas) is the spot price from the TTF (Title Transfer Facility) trading hub[1]. The coal price (€/ton.) is the spot index API#2 (CIF ARA[2]). The EUA price series (€/ton.) is the future price quoted at EEX – European Energy Exchange (Leipzig, Germany)[3]. We transformed the price variables into their natural logarithms to reduce variability, thus obtaining directly the elasticity values from the parameter estimates.

Table 2. Summary Statistics

	Main Variables - Prices						Control Variables					
	Electricity			Inputs			Temp.		Production Technologies			
	Peak	Base	Off-peak	Carbon	Gas	Coal	CDD	HDD	Renew	Hydro	CCGT	Coal
units	*€/MWh*	*€/MWh*	*€/MWh*	*€/Ton.*	*€/MWh*	*€/Ton.*	*ºC*	*ºC*	*%*	*%*	*%*	*%*
Mean	52,20	48,01	43,83	15,92	19,31	76,78	1,41	2,28	0,03	0,19	0,58	0,17
Median	50,72	46,93	42,92	14,80	21,40	78,62	-	-	0,01	0,14	0,64	0,11
Min.	3,47	4,62	5,78	6,90	7,00	42,46	-	-	0,00	0,00	0,00	0,00
Max.	93,67	82,13	72,98	29,27	31,49	141,91	8,64	13,43	0,70	0,87	0,97	0,83
Std. Dev.	14,60	13,47	12,72	4,55	5,89	22,32	2,28	3,10	0,11	0,16	0,27	0,18
Var.Coef.	0,28	0,28	0,29	0,29	0,31	0,29	1,62	1,36	3,25	0,89	0,46	1,07
Skewness	0,33	0,17	-0,03	0,93	-0,37	0,51	1,32	1,19	4,74	1,60	-0,67	1,39
Kurtosis	-0,16	-0,29	-0,29	0,26	-1,01	-0,08	0,31	0,38	21,60	2,77	-0,61	1,44

Source: Electricity prices - OMEL; Inputs (fuel prices and EUA price) - Thomson Reuters/DataStream; Air temperatures - European Climate Assessment & Dataset (ECA&D); Production technologies: OMEL.

As shown by Engle et al. (1986) as well as by other studies - Fezzi and Bunn (2010), Fezzi and Bunn (2009) and Fell (2010), including for the Spanish case (Labandeira et al., 2012; Valor et al., 2001) -, the relationship between electricity demand and air temperature is non-linear ("V" shaped function) as it is used for both heating or cooling purposes. Therefore, in order to consider that non-linear relationship between electricity demand and air temperature, we modeled temperature as a deviation from a threshold. We defined two climate variables: *HDD* (heating degree days), which represents the deviations of mean temperature below the threshold of cold (increasing of electricity demand is mainly for heating purposes), and *CDD* (cooling degree days), which represents the deviations above the threshold of heat (increasing of electricity demand is mainly for cooling purposes).[4] We used the thresholds proposed by Labandeira et al. (2012) for the Spanish case, considering the level of 13 ºC for *HDD* and 23ºC for *CDD*.

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[1] TTF in Netherlands is one of the most important trading hubs in Europe; physical natural gas delivery at national trading point, the Dutch Title Transfer Facility.

[2] Delivered to the Amsterdam/Rotterdam/Antwerp region.

[3] We selected the future price because this is the only price series of EUA 2nd Phase that starts on January 1st, 2008. However, we tested prices from other markets (futures and spot), namely ECX – European Climate Exchange (London, UK) and BlueNext (Paris, France), and we did not find significant differences.

[4] HDD = max (T^* - T_t; 0) and CDD = max (T_t - T^{**}; 0), with T_t representing the mean daily temperature, T^* the cold threshold and T^{**} heat threshold.

To control the model for the marginal technology in the market, we defined four variables according to the merit order present in the Spanish power generation mix: renewables, hydroelectric, thermal coal and combined cycle gas turbine (CCGT) are the usual marginal technologies[5]. Each variable "mix_t^m" is defined as the ratio between the power generated by the technology "*m*" bided/matched over 95% of the marginal price and the total amount of power in the market bided/matched over 95% of the marginal price. For instance, the variable $mix_t^{coal} =$ 0,25 means that, on day *t*, 25% of all electricity bided/matched over 95% of the marginal price was produced by coal-fired power plants. These variables, like the air temperature variables, are treated in the econometric model as exogenous variables.

5. Model Description

It is becoming well known that dynamic interactions may be important in the price formation process of electricity as shown by Knitell and Roberts (2005). In understanding the interation of electricity and input prices, there are many complex relationships to consider. For instance, given the marginal tecnologies present in the Spanish electricity system, it would appear likely that coal and natural gas prices influence electricity prices, and EUA prices are influenced by coal and natural gas prices as shown by Mansanet-Bataller et al. (2007) and Alberola et al. (2008). The multivariate approach of simultaneous equations is well suited to handle with the possible endogeneity problems which could arise from those interactions. With this econometric technique all price variables in the model are treated as endogenous.

Multivariate analysis has been developed using either the vector autoregressive (VAR) models or cointegrated VAR models. The cointegration concept, introduced by Engle and Granger (1987), means that individual economic variables may be non-stationary and wander through time, but a linear combination of them may converge to a stationary process. Such a process, if present, may reflect the long-run equilibrium relationship, and it is referred to as the cointegration equation. As noted in Engle and Granger (1987), there are strong beliefs that economic data are non-stationary which can lead to spurious regression results. Removing the non-stationarity by differencing the variables may impose the risk of losing relevant information about long-term relationships. Alternatively, the VAR can be improved to handle cointegrated variables in what is commonly referred as a VECM. This latter alternative, if it is possible, has the advantage of allowing the simultaneous analysis of the long-run interactions and the short-term adjustments to the equilibrium relationship.

The specification in this study follows Johansen and Juselius (1990) and Johansen (1991). Assuming the existence of cointegration, the data generating process P_t can be appropriately modeled as a VECM with $k-1$ lags (which is derived from a levels VAR of order *k*). Consider a VAR of order *k* with a deterministic part given by μ_t. One can write the *p-variate* process as $P_t = \mu_t + A_1P_{t-1} + A_2P_{t-2} + \ldots + A_kP_{t-k} + \varepsilon_t$.

Taking the variables in first differences, with Δ as the difference operator ($\Delta P = P_t - P_{t-1}$), than $P_{t-i} \equiv P_{t-1} - (\Delta P_{t-1} + \Delta P_{t-2} + \ldots + \Delta P_{t-i+1})$ and one can re-write the process as:

$$\Delta P_t = \Pi P_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta P_{t-i} + \mu_t + \varepsilon_t \tag{1}$$

Where: $\Pi = \sum_{i=1}^{k} A_i - I$; $\Gamma_i = -\sum_{j=i+1}^{k} A_j$ and $\varepsilon_t \sim Niid(0, \Sigma)$

[5] We excluded the thermal fuel because it has represented the marginal technology at very few situations. Moreover in the econometric model it is not statistical significant.

In Eq. (1) P_t represents a vector of p non-stationary endogenous variables and the matrix Π contains information about the long-run relationship among endogenous variables and can be decomposed as $\Pi = \alpha \beta'$, whereas β represents the cointegration vectors and α the matrix with the estimations on the speed of adjustment to the equilibrium. The matrix Π is called an error correction term, which compensates for the long-run information lost through differencing. The rank of matrix Π (r) determines the long-run relationship. If the rank of the matrix Π is zero ($r = 0$), there is no long-run relationship and the model above is equal to a VAR in differences. If the matrix Π has the full rank $(r = p)$, then it is invertible, meaning that the processes P_t is stationary I(0) and a normal VAR in levels can be used. The cointegration relationship occurs when the order of the matrix is between 0 and p ($0 < r < p$) and there are (pxr) matrices α and β such that the equation $\Pi = \alpha \beta'$ holds. In this case, P_t is integrated of first order I(1) but the linear combination $X_t = \beta' P_t$ is I(0). If, for example, $r = 1$ and the first element of β was $\beta = -1$, then one could write the linear combination as $X_t = -P_{1,t} + \beta_2 P_{2,t} + \ldots + \beta_p P_{p,t}$, which is equivalent to saying that long-run equilibrium relationship among variables of vector P_t is expressed as $P_{1,t} = \beta_2 P_{2,t} + \ldots + \beta_p P_{p,t} - X_t$. This long-run relationship may not holds all the time, however the deviation X_t are stationary I(0). In this case, Eq. (1) can be written as:

$$\Delta P_t = \alpha\beta' P_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta P_{t-1} + \mu_t + \varepsilon_t \tag{2}$$

This approach was extended later by Harbo et al. (1998) and Pesaran et al. (2000) to include exogenous variables in the model. This in our case is particularly useful because it allows an adequate treatment of the marginal technology and temperature variables.

In our case a general VECM specification can be formulated as:

$$\Delta P_t = \alpha\beta' P_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta P_{t-1} + \Phi Z_t + \mu_t + \varepsilon_t \tag{3}$$

- Where P_t is a (4x1) vector of prices (endogenous variables) measured at time t: $P_t = [P_t^{peak}, P_t^{carb}, P_t^{gas}, P_t^{coal}]$ - P_t^{peak} is the natural logarithm of electricity price, P_t^{carb} is the natural logarithm of CO_2 emission allowances price, P_t^{gas} is the natural logarithm of natural gas price and P_t^{coal} is the natural logarithm of coal price. α and β are (4xr)[6] matrix, whereas β and α represent, respectively, the cointegrating vectors and the matrix with the estimations on the speed of adjustments to the equilibrium.
- Where Γ_i is a (4x4) matrix with the estimations of short-run parameters relating price changes lagged i periods.
- Where Φ is a (4x6) matrix of coefficients associated with the (6x1) vector Z_t that represents the exogenous variables: $Z_t = [mix_t^{renew}, mix_t^{hydro}, mix_t^{ccgt}, mix_t^{coal}, CDD, HDD]$ - mix_t^{renew} is the % of electricity bided/matched over 95% of the marginal price on day t produced by renewables, mix_t^{hydro} produced by hydroelectric power plants, mix_t^{ccgt} produced by CCGT power plants, mix_t^{coal} produced by coal-fired power plants, and the air temperature variables (*HDD* and *CDD*) as defined previously.
- Where μ_t is a (4x1) vector of constant[7] and ε_t is a (4x1) vector of innovations.

[6] Where r is the number of cointegrating vectors.

[7] Actually $\Pi = \alpha \beta'$ may be of order (4x5) or (4x4) depending on whether the constant is inside or outside (restricted or unrestricted) of the cointegration space.

6. Empirical Results

6.1 Unit Root and Cointegration Tests

We started our estimation procedure by testing the non-stationarity for all price series. We tested the null hypotheses of a unit root (UR) trough the Augmented Dickey-Fuller Test (ADF test) and the null of stationarity trough Kwiatkowski, Phillips, Schmidt and Shin test (KPSS test). The tests were conducted using the natural logarithms of the price series (electricity, EUA, natural gas and coal). As shown in Table 3, all series fail to reject the null of a UR for all specifications tested at a 5% level except for electricity price (ADF Test with only a constant). However, the Unit Root Test with Breaks, which allows accounting for the possibility of level shift (Lanne et al., 2002), and the KPSS test confirm the non-stationarity of the electricity prices. On the contrary, we have evidence that the differenced series are stationary (evidence less strong in the case of electricity price - KPSS test). These results provide evidence for the hypotheses that all prices are non-stationary in levels, but have stationary first differences.

Table 3. Unit Root Tests

	ADF Test					KPSS Test			UR Test With Breaks		
Natural Logarithm of Prices – Levels											
	Lags	Constant		Const.&Trend.		Lags	Constant			Lags	Constant
		Stat.	p-value	Stat.	p-value		Stat.				Stat.
P^{peak}	6	-2,925	0,04	-2,860	0,18	7	2,858	***	P^{peak}	6	-1,170
P^{carb}	0	-0,487	0,89	-1,306	0,89	7	5,330	***	P^{carb}	0	0,264
P^{gas}	0	-1,996	0,29	-2,011	0,59	7	2,361	***	P^{gas}	0	-1,987
P^{coal}	0	-1,116	0,71	-1,119	0,92	7	2,260	***	P^{coal}	0	-1,044
Natural Logarithm of Prices - First Differences											
	Lags	Constant		No Constant		Lags	Constant				
		Stat.	p-value	Stat.	p-value		Stat.				
ΔP^{peak}	5	-18,491	0,00	-18,498	0,00	7	0,039	*			
ΔP^{carb}	0	-29,456	0,00	-29,409	0,00	7	0,149				
ΔP^{gas}	0	-32,672	0,00	-32,688	0,00	7	0,107				
ΔP^{coal}	0	-30,741	0,00	-30,756	0,00	7	0,247				

Notes: Null hypotheses of a unit root (the series is non-stationary) for ADF test and Unit Root With Breaks test. Null hypotheses of stationarity for KPSS test. Critical values and p-values for ADF test are given in MacKinnon (1996). Critical values for the KPSS test are given in Kwiatkowski et al. (1992): 0,347; 0,463 and 0,739 for 10%, 5% and 1% significant level respectively. Critical values for UR With Breaks test are given in Lanne et al. (2002): -2,58; -2,88 and -3,48 for 10%, 5% and 1% significant level respectively. Number of lags chosen by SIC minimization (maximum of 20 lags) for ADF and UR tests. Number of lags for the KPSS test as $4^*(T/100)^{1/4}$. *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

The first step in modeling procedure is to determine the lag relationship among the price series in the levels VAR. The AIC (Akaike Info Criterion), SIC (Schwarz Info Criterion) and HQC (Hannan and Quinn Criterion) loss metrics suggest the appropriate VAR lag length is two[8] *(k=2)*, indicate that the inclusion of exogenous variables (both the generation mix variables and weather variables) improves the fit of the VAR to the data, and suggest not including lags in the exogenous variables.

The tests of cointegration were implemented with the technique based on the reduced rank regression introduced in Johansen (1991). Since the VAR model contains exogenous variables, the Osterwald-Lenum (1992) and Johansen (1995) asymptotic critical values are no longer valid;

[8] As the VAR is specified in first differences, the number of lags lag in the VECM should be one (*k-1*).

therefore we used the asymptotic critical values provided in Mackinnon et al. (1999). The decision of whether the constant is within or outside of the cointegration space was based on the three metrics, and the results recommend restricting the intercept to lie in the cointegration space.

Table 4. Cointegration Tests

H_O:		Trace Test			λ_{max} - Max Eigen Value Test		
r =	p-r =	Statistics	Critical Values	p-values	Statistics	Critical Values	p-values
0	4	158,67	109,82	0,00	113,18	47,63	0,00
1	3	45,49	78,33	0,93	34,21	40,98	0,22
2	2	11,29	50,57	1,00	8,18	34,00	1,00
3	1	3,11	26,14	1,00	3,11	26,14	1,00

Notes: 5% significant level for critical values. p-values calculated using the software in Mackinnon et al. (1999). Model with restricted constant, two lags in endogenous variables and 6 exogenous variables.

The results for both Trace Test and λ_{max} Statistics, presented in Table 4, clearly indicate the existence of one cointegrated vector (r = 1). So, we proceed under the result of a single long-run relationship among the variables.

6.2 VECM Estimation

With the cointegration rank and optimum number of lags determined, the parameters of model can be estimated. The results reported in Table 5 for the cointegrated vector β, which is normalized on P_{t-1}^{peak}, show that all estimated parameters have the correct sign and they are all significant (at 10% significance level) according to the Likelihood Ratio Test as showed in Johansen (1995). Since the coefficients can be interpreted as price elasticities, a EUA price rise of 1%, would, in equilibrium, be associated with an electricity price rise of 0,27% (0,25% in the natural gas price and 0,27% in coal price). This pass-through rate of CO_2 costs into electricity prices of 27% compares with the estimate of 93% in Honkatukia et al. (2006) for the NordPool market, 32% in Fezzi and Bunn (2009) for the UK market, [11%-13%] in Fell (2010) for the NordPool market, 36% in Thoenes (2011) for the German market and 51% in Freitas and Silva (2013) for the Portuguese market. In addition, the results we found are below the simulations for the Spanish market of [60%-63%] in Sijm et al. (2008) and [60%-100%] in Lise et al. (2010).

Analyzing the short-run parameters in the VAR, only the lagged electricity price is significant. In the case of the exogenous variables, we could confirm that the marginal technology is important for the short run dynamics of electricity price. There is also strong evidence that the weather variables are important for electricity price changes in the short-run, when the demand of electricity reflects either heating (*HDD*) or cooling (*CDD*) purposes.

Table 5. VECM Parameter Estimates

Cointegration Relationship				
P_t^{peak}	P_t^{carb}	P_t^{gas}	P_t^{coal}	*Const.*
1,000	-0,268 ***	-0,253 **	-0,272 *	-2,397 ***
	(0,080)	(0,107)	(0,136)	(0,530)

Short Run Dynamics	ΔP_t^{peak}	ΔP_t^{carb}	ΔP_t^{gas}	ΔP_t^{coal}
EC_{t-1}	-0,194 ***	-	-	-0,007 *
ΔP_{t-1}^{peak}	-0,332 ***	0,016 **	-	-
ΔP_{t-1}^{carb}	-	0,074 **	0,110 **	0,104 ***
ΔP_{t-1}^{gas}	-	-0,031 *	-	0,030 *
ΔP_{t-1}^{coal}	-	-0,113 ***	-	-
mix_t^{renew}	-0,622 ***	-	-	-
mix_t^{hydro}	-0,169 ***	-	-	-
mix_t^{ccgt}	-0,237 ***	-	-	-
mix_t^{coal}	-0,229 ***	-	-	-
CDD	0,002 **	-	-	-
HDD	0,002 **	-	-	-

Notes: EC_{t-1} refers to the adjustment coefficients (α). We only present the significant coefficients. Standard errors in parentheses. *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

Table 6. Exclusion and Exogeneity Tests

	Exclusion		Weak Exogeneity	
	Stat.	p-value	Stat.	p-value
P^{peak}	78,18	0,00	78,7	0,00
P^{carb}	10,74	0,00	1,13	0,29
P^{gas}	3,58	0,06	0,97	0,32
P^{coal}	3,04	0,08	2,90	0,09
Const.	16,69	0,00		

A weak exogeneity test is performed (Juselius, 2006), which tests the null hypothesis that each of the series does not respond to the innovations or shocks in the cointegration space, i. e. that the series is unresponsive to the deviations from the long-run relationships. This test is performed on α, more specifically, for one particular series we test whether the corresponding row in matrix α is zero. According to the results reported in Table 6, for 5% significance, only the electricity price series rejects the null, meaning that the long-run relationships in the data are important only for the electricity price. These results are expected since EUA, natural gas and coal are commodities traded global and thus may be driven more by forces outsider the Spanish energy market. As one can see, the evidence of weak exogeneity is not so strong in the case of coal prices. Further, an exclusion test is performed (Juselius, 2006), which tests the null hypothesis that a particular series is not in the cointegration space. This test is performed on β, also here test for a zero row. As we can see (Table 6), at 5% significance level, all series reject the null, meaning that all the coefficients are strongly significant. Hence, there is strong evidence that all the price series are important to define the equilibrium vector, i.e. EUA, gas and coal prices are essential to define the level to which electricity price is attracted over time[9].

Table 7. Diagnostic Tests on Residu**als**

Diagnostic Tests on Residuals		
Serial Correlation [H_0: uncorrelated]		
Ljung-Box Q' (5) =	6,81	[0,235]
Heterocedasticity [H_0: homokedastic]		
ARCH (5) =	91,4	[0,000]
Normality (H_0: normal distributed)		
Doornik-Hansen (8) =	5.340	[0,000]

Notes: p-values in parentheses.

Table 8. Residuals Correlation Matrix

ΔP^{peak}	1	0,026	0,005	-0,038
ΔP^{carb}	-	1	0,108	-0,039
ΔP^{gas}	-	-	1	0,065
ΔP^{coal}	-	-	-	1

9 An exclusion test is also performed on the constant term, which results in a rejection of the null hypothesis. This agrees with the inclusion of the constant parameter in the cointegration space.

Although residual analysis (Table 7) shows evidence of autoregressive conditional heterocedasticity (ARCH) and non-normality this is not likely to be a major problem in our cointegration analysis since Gonzalo (1994) showed that the properties of asymptotically optimal inferences present on maximum likelihood estimators hold in finite samples even without the normality assumption. Observing the residuals correlation matrix (Table 8) we can see that the correlations among all equations are very low.

Table 9. Results for Different Regimes Load

Price of Electricity: peakload				
P_t^{peak}	P_t^{carb}	P_t^{gas}	P_t^{coal}	*Const.*
1,000	-0,268 ***	-0,253 **	-0,272 *	-2,397 ***
	(0,080)	(0,107)	(0,136)	(0,530)
EC_{t-1} = -0,194 ***				
Price of Electricity: baseload				
P_t^{base}	P_t^{carb}	P_t^{gas}	P_t^{coal}	*Const.*
1,000	-0,207 ***	-0,303 ***	-0,253 **	-2,051 ***
	(0,062)	(0,083)	(0,106)	(0,412)
EC_{t-1} = -0232 ***				
Price of Electricity: off-peakload				
$P_t^{off\text{-}peak}$	P_t^{carb}	P_t^{gas}	P_t^{coal}	*Const.*
1,000	-0,167 ***	-0,362 ***	-0,205 **	-1,897 ***
	(0,056)	(0,076)	(0,100)	(0,373)
EC_{t-1} = -0,323 ***				

Notes: EC_{t-1} refers to the adjustment coefficients (α). *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

In Table 9 we report the results for the strategy implemented to conclude for significant differences in the pass-through rate of CO_2 cost into the electricity price due to differences in the marginal generation technology. Therefore, we estimated three alternative models defined according to electricity load regimes (peakload, baseload and off-peakload), assuming that in each regime prevails a distinct marginal generation technology. An interesting, and maybe an expected result, is that the PTR of CO_2 is higher (lower) when the PTR of coal is higher (lower), meaning that the coal thermal probably is the prevailing technology at the high load periods and is accountable for the higher sensibility of electricity price to the carbon costs at those periods of day. Finally the CCGT tends to be the marginal technology for low-load periods, associated with a lower sensitivity of electricity price to the CO_2 costs.

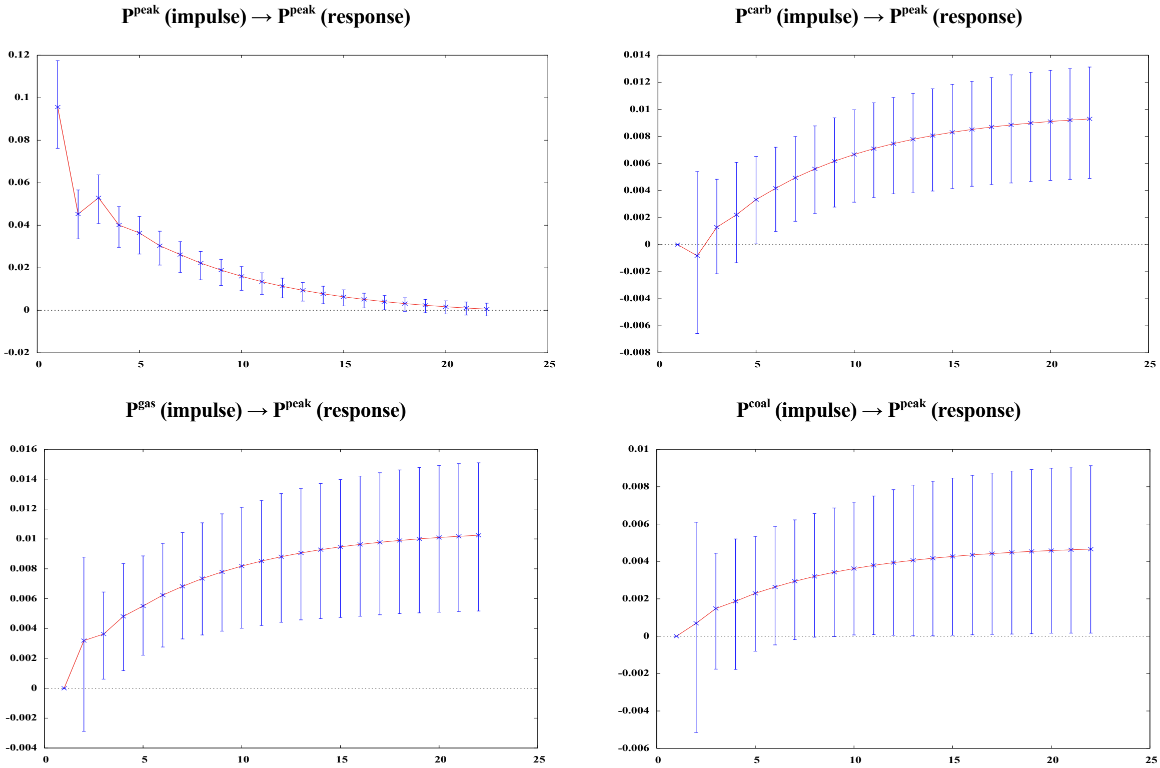
6.3 Impulse Response Analysis

The relationship between the variables can be illustrated graphically with an impulse response analysis. The functions in Fig. 1 measure the impact of an exogenous price shock of one variable for a period of one month (22 working days). The responses are normalized, meaning that each response is divided by the standard error of the innovations of that series, which allows the comparison of the series. Therefore, each shock has the magnitude of one standard error[10]. Impulse response functions (IRF) of electricity prices to one-time shocks in the input prices

[10] To account for contemporaneous correlation in the error terms, the innovations are orthogonalized according to the Cholesky standard decomposition approach.

(carbon, gas and coal) with bootstrapped confidence intervals (2,5% and 97,5% quintiles) are showed in Fig. 1. The IRF show that the input prices have a strong, positive and persistent effect on the electricity price. Once the shocks have settled (about ten/fifteen working days), the effects are consistent with the cointegration relationship, meaning that the long-run equilibrium is reached roughly two/three weeks after the shock or innovation. The response to a shock in the carbon price starts to be opposite to the long-run relationship, but only for a short period of time. A similar effect was reported in Thoenes (2011). The IRF also show that the impact of an electricity price shock on the electricity price itself decays quickly and it isn`t persistent, meaning that electricity price shocks are probably driven by capacity effects.

Fig. 1 - VECM Orthogonal Impulse Responses with Bootsptrapped Confidence Intervals



Notes: Impulse Response for one standard deviation innovation (shock). Days on x-axis and responses on y-axis.

7. Conclusion

We analyzed the impact of CO_2 emission allowances price on the Spanish electricity market using a co-integrated vector error correction model. This econometric approach encompasses long-run equilibrium relations and short-run effects in the dynamic interactions between electricity price and input prices (carbon, natural gas and coal). The effect of the input prices in electricity price was controlled through a set of exogenous variables reflecting the demand for electricity conditions and the marginal technology present in the electricity system. The model was estimated using daily data from Phase II of the EU ETS. We estimated a dynamic pass-through rate of carbon price into electricity price of 27%, meaning that a 1% shock in carbon price impact into a 0,27% shock in electricity price in the long-run. By testing different models for the three load regimes (peakload, off-peakload and baseload), this study found strong evidence of time-varying electricity price responsiveness to carbon price shocks. The marginal pass-through rate is higher in peak than in off-peak hours, β_{carb} = 27% and β_{carb} = 17%

respectively. We also showed that carbon price plays an important role in formulating the equilibrium price of electricity and, as the other fuels, is essential exogenous in the long run.

The empirical results found in this study support the hypothesis that power producers have been passed on the opportunity cost of freely allocated emission allowances to electricity price, enabling power companies to get windfall profits. So, we may conclude that power producers competitiveness would not be affected if they had paid for the emissions allowances.

Acknowledgments

The authors acknowledge the freely provided data on weather: Klein Tank, A.M.G. and Coauthors, 2002. Daily dataset of 20th-century surface air temperature and precipitation series for the European Climate Assessment Int. J. of Climatol., 22, 1441-1453. The second author would like to acknowledge that this work has been partially supported by FCT under project grant PEst-C/EEI/UI0308/2011 and the Energy for Sustainability Initiative of the University of Coimbra and supported by the R&D Project EMSURE (Energy and Mobility for Sustainable Regions) – CENTRO 07 0224 FEDER 002004.

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