European Union emissions trading scheme impact on the Spanish electricity price during phase II and phase III implementation

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Abstract

The European Union Emissions Trading Scheme (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 includes all Phase II of the EU ETS and the first year of Phase III implementation, from January 2008 to December 2013. 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. The four commodities prices are modeled as joint endogenous variables with air temperature and renewable energy as exogenous variables. We found a long-run relationship (cointegration) between electricity price, carbon price, and fuel prices. By estimating the dynamic pass-through of carbon price into electricity price for different periods of our sample, it is possible to observe the weakening of the link between carbon and electricity prices as a result from the collapse on CO_2 prices, therefore compromising the efficacy of the system to reach proposed environmental goals. This conclusion is in line with the need to shape new policies within the framework of the EU ETS that prevent excessive low prices for carbon over extended periods of time.

JEL codes

Q58; H23; Q48; C32; L94

Keywords

Environmental policy; Carbon emissions; Electricity prices; Cointegration; Vector error correction model

1. Introduction

The European Union Emissions Trading Scheme (EU ETS) is the first international system for trading greenhouse gas emission allowances. The EU ETS works based on the 'cap-and-trade' principle. Among the several industries covered by the scheme, the electricity sector is the largest one. Launched in 2005, implementation of the EU ETS was set to run in three phases: the first (pilot phase) ranging from 2005 to 2007, the second from 2008 to 2012 and now in its third phase, running from 2013 to 2020. Economic theory explains why under a 'cap-and-trade' system, the price of emissions ought to be treated as a marginal cost. As a producer holds allowances, the electricity production and CO_2 emission compete with the possibility of selling those allowances in the market. Therefore, according to the economic theory, energy producers are expected to add this new cost to their marginal production cost whether or not CO_2 allowances are granted for free. This so-called CO_2 opportunity cost equals the CO_2 market price. Adding the opportunity cost of carbon to the other costs of energy generation and passing these costs through to the electricity price is a necessary condition for achieving the environmental targets in a cost-efficient way (that is, guaranteeing that the emission cuts would be made by those firms that could achieve the most efficient abatement costs).

Thus, the efficiency of the EU ETS in providing incentives both to the energy producers (to reduce their emissions by switching to or investing in technologies with lower emissions) and energy consumers (to reduce their demand of electricity by increasing their energy efficiency) depends on whether or not CO_2 costs may be passed through to electricity prices. We therefore investigate as our research problem the interaction between the electricity markets and carbon markets trying to find out how the EU ETS impacts the price of electricity. Our specific research questions are: Does the carbon price have an impact on the Spanish electricity price? Do the prices of electricity and carbon (and other fuels used in electricity generation) share a common trend?

The theoretical foundation of the CO_2 cost pass-through to electricity prices is well established in the scientific literature, as presented by Sijm et al. (2006) in the context of perfect competition, and by Bonacina and Gulli (2007) for markets under imperfect competition. While electricity producers may fully recognize the opportunity costs of CO_2 allowances in their marginal production costs, these costs might not be fully passed through to electricity prices. Sijm et al. (2005) and Gullì (2008) offer a set of explanations for the pass-through rate of CO_2 costs into electricity prices that may differ by 100%, including among other reasons demand response (price elasticity), level of energy demand (peak-load vs. off-peak-load), market structure (degree of market concentration), technology mix (fuel used in production), and available generation capacity.

This paper builds on previous work by the authors for the Portuguese Electricity Market (Freitas and Silva, 2013 and Freitas and Silva, 2012) on the complementary division of Iberian Electricity Market (MIBEL). According to our knowledge, we believe this study is an innovative contribution to the state of the art due to the fact that our research embodies the first empirical study of the Spanish market for the complete Phase II of the EU ETS, as well as the first empirical study on the European market to include results from the Phase III of the system. Moreover, the econometric treatment given to renewable energy within the model alongside carbon and fuel prices represents an important contribution considering the growing significance of these technologies in the Spanish energy mix. This paper is structured as follows. Section 2 presents a brief literature review. Section 3 describes the functioning of the Spanish electricity market and presents the data set. Section 4 describes the methodological approach. Section 5 presents the empirical findings. Section 6 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). Initial published analyses conducted in order to estimate the pass-through rate 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. The first studies taking those interdependencies into account through multivariate analysis, where all prices are modeled as a joint system, were provided by Honkatukia et al. (2006) and Fezzi and Bunn (2009). Developing a Vector Error Correction Model (VECM), with the electricity, gas and carbon prices modeled jointly as endogenous variables, and temperature as an exogenous regressor, Fezzi and Bunn (2009) estimated the dynamic pass-through of CO_2 price into electricity price for Germany and the UK. Honkatukia et al. (2006) developed a similar model for the NordPool market considering the electricity, gas, coal, and carbon prices as endogenous variables. Other studies, including this one, have followed that econometric approach. 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. Thoenes (2011) analyzed the relationship among electricity, fuels, and carbon prices for the German market, also with a VECM. Honkatukia et al., 2006, Fezzi and Bunn, 2009, Fell, 2010 and Thoenes, 2011, and Freitas and Silva (2013) found a long-run cointegrating equilibrium among electricity, fuels, and carbon prices. Chemarin et al. (2008) estimated a VECM to the French energy market considering electricity, gas, oil, and carbon prices as endogenous and two different weather variables: temperature (affecting the demand side of electricity market) and rainfall (influencing the electricity production of a country concerning its energy mix). The authors found that there is no short-run relationship between electricity returns and carbon returns, while there is a long-run relationship. Pinho and Madaleno (2011) examine the interactions between carbon, electricity, and fossil fuel (coal, oil, and natural gas) returns for Germany, France, and Nordic countries. They analyzed the effect of nuclear power generation using a VECM and found it could limit increases in electricity prices as a result of increased carbon prices.

Mohammadi (2009) analyzes the relation between the electricity prices and coal, natural gas, and crude oil prices for the United States (US) market finding, a long-run relationship between electricity and coal prices. Also for the US market, Mjelde and Bessler (2009) added the uranium price to the analysis and controlled for weather effects with temperature variables similar to those used in our model. They concluded that in the long run the price of electricity is influenced by the fuels market as these prices are weakly exogenous, except for uranium.

Ferkingstad et al. (2011), for the Northern European electricity markets, studied the dynamics between electricity and fuel prices (oil, natural gas, and coal) with wind power and water reservoir level as exogenous variables. Using a VECM and a Linear non-Gaussian Acyclic Model (LinGAM), they concluded that in the long run, electricity and natural gas prices are interlinked. Moutinho et al. (2011) focused the Spanish power market, same as our study, but for an earlier period (2002–2005). Based on a cointegration approach, they concluded that electricity price is explained by the evolution of natural gas prices.

Cotton and Mello (2014) analyzed the efficiency of the Australian Emission Trading Scheme using a long-run structural modeling technique. They applied a generalized forecast error variance decomposition, finding that emissions prices have little effect on electricity prices.

Jouvet and Solier (2013) used a first order autoregressive model to assess the cost pass-through of CO_2 into electricity prices. Their results indicated that while energy producers pass through the carbon cost during Phase I, the relationship between CO_2 costs and marginal costs of electricity seems to be less evident over the second phase due to the global financial crises. Aatola et al. (2013), for a set of European countries, concluded that the carbon price has a positive but uneven impact on electricity prices. Boersen and Scholtens (2014), employing a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model concluded, for the NordPool market, that the price of electricity is partly determined by the cost of the fuel inputs (natural gas and oil prices) and these costs are affected by EUA prices.

With respect to the recent behavior of the carbon market and impacts on the electricity sector the recent works of Van den Bergh et al., 2013 and Fagiani et al., 2014 and Koch et al. (2014) identified a set of reasons that might explain the CO_2 price fall observed in recent years. These factors include economic recession, renewable policies and the use of international green certificates. Also, the impact of new developments in energy commodities markets on the price of CO_2, namely the availability of cheap gas (shale gas), has been emphasized by some authors (Glachant and Ruester, 2014).

3. Spanish electricity market and data

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 the 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. A single Iberian price applies if there is no congestion in the interconnection between Spain and Portugal and distinct prices apply if there is congestion in the interconnection between the countries (Silva and Soares, 2008). Table 1 shows the evolution of the total installed capacity and production by technology from 2008 to 2012.

Table 1.
Electricity production and generation capacity by technology.

	Installed capacity (MW)				Electricity production (GWh)			
	2008		2012		2008		2012	
Nuclear	7716	8.5%	7853	7.7%	58,973	21.2%	61,470	22.9%
Hydroelectric	16,657	18.3%	17,761	17.4%	21,428	7.7%	19,455	7.2%
Thermal fuel/gas	4418	4.9%	520	0.5%	2378	0.9%	0	0.0%
Thermal coal	11,359	12.5%	11,248	11.0%	46,275	16.6%	54,721	20.4%
CCGT (natural gas)	21,675	23.9%	25,340	24.9%	91,286	32.8%	38,593	14.4%
Total ordinary regime	61,825	68.0%	62,722	61.6%	220,340	79.2%	174,239	64.9%
Wind	15,874	17.5%	22,573	22.2%	31,393	11.3%	48,103	17.9%
Other renewables	6048	6.7%	9293	9.1%	11,599	4.2%	20,608	7.7%
Other non-renewables	7132	7.8%	7240	7.1%	23,308	8.4%	33,442	12.5%
Total special regime	29,054	32.0%	39,106	38.4%	66,300	23.8%	102,153	38.0%
Generation consumption					−8338	−3.0%	−7889	−2.9%
Total	90,879		101,828		278,302	100%	268,503	100%
International balance					−3731		−11,770	
Pumped storage consumption					−11,040		−5023	
Total demand					263,531		251,710	

Source: Red Eléctrica de España: "The Spanish Electricity System 2008" and "The Spanish Electricity System 2012". Data for Peninsular electricity system. CCGT – combined cycle gas turbine.

Table 2.
Summary statistics.

	Endogenous Variables – Prices						Exogenous Variables			
	Electricity			Inputs			Renewables		Temperature	
	Base	Peak	Off-peak	Carbon	Gas	Coal	Hydro	Wind	CDD	HDD
Unit	€/MWh	€/MWh	€/MWh	€/Ton.	€/MWh	€/Ton.	Index	Index	°C	°C
Mean	48.27	52.47	44.08	14.23	20.43	75.93	0.79	1.01	0.82	1.90
Median	48.34	52.19	44.30	14.17	22.49	73.85	0.76	0.99		
Maximum	82.13	93.67	72.98	29.33	37.75	141.91	1.72	1.52	7.85	12.55
Minimum	4.62	3.47	5.78	5.99	7.00	42.46	0.16	0.70		
Std. Dev.	12.48	13.45	11.95	5.29	5.81	20.20	0.36	0.17	1.55	2.78
Coef. Var.	0.26	0.26	0.27	0.37	0.28	0.27	0.46	0.17	1.88	1.46
Skewness	0.09	0.26	−0.12	0.65	−0.63	0.69	0.29	0.55	1.85	1.37
Kurtosis	0.03	0.22	−0.05	−0.03	−0.65	0.64	−0.48	0.23	2.52	0.88

Sources: Electricity prices – OMEL; Inputs (fuel prices and EUA price) - Thomson Reuters/DataStream; Renewable Indexes (Hydro and Wind) - Red Eléctrica de España; Air temperatures - European Climate Assessment & Dataset (ECA&D). Population – Eurostat.

Considering the data presented in Table 1, produced renewable energy, particularly hydroelectric and wind energy, play a crucial role on the Spanish energy mix. Therefore, it is likely to observe an impact on electricity market prices during periods of high intensity supply from hydro and wind resources. This influence has already been presented by Gelabert et al. (2011) for the Spanish electricity market, where the authors concluded that a marginal increment of 1 GWh of electricity from renewable sources would lead to a reduction in electricity prices of 2€/MWh.

The present work focuses first on the entire Phase II of the EU ETS, ranging from January 2008 to December 2012. Later, this analysis will be extended to the first year of Phase III, from January to December 2013. Daily data for working days is used (weekend and national holidays are excluded because of significantly distinct demand). The electricity series from OMEL are the day-ahead prices (€/MWh) for the three load regimes: peak load, off-peak load, and base load. The peak price is the hourly average of spot prices quoted from 8:00 h to 20:00 h, 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 spot price quoted at European Energy Exchange (EEX, Leipzig, Germany). We transformed the price variables into their natural logarithms to reduce variability, thus obtaining directly the elasticity values from the parameter estimates (Table 2).

As previously stated, the analysis of the relationship between electricity and production input prices (i.e., CO_2 emission permits, natural gas, and coal) must be controlled by the intensity of renewable energy on the market. The selected variables to represent the quantity of electricity from hydro and wind sources are: Hydroelectric Productibility Index (*Hydro*) and Wind Power Productibility Index (*Wind*). These indexes are the quotient between the electricity produced by the hydroelectric/wind technology for a period of time and the historical average, both related to the same period (month) and to the same hydroelectric equipment. [3]

Climate variables (such as temperature or rainfall) may also influence the relationship between electricity and carbon prices. As shown by Engle et al. (1986) as well as by Fezzi and Bunn, 2009 and Fell, 2010, and Blázquez et al. (2013) for the Spanish case, the relationship between electricity demand and air temperature is non-linear (a “V” shaped function) as electricity is used for both heating and cooling purposes. We therefore 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 electricity demand is mainly for heating purposes), and *CDD* (cooling degree days), which represents the deviations above the threshold of heat (increasing electricity demand is mainly for cooling purposes). [4] We used the thresholds proposed by Blázquez et al. (2013) for the Spanish case, considering the level of 15 °C for *HDD* and 22 °C for *CDD*. These variables, like produced renewable energy, are treated in the econometric model as exogenous variables.

In Fig. 1 we can observe the significant seasonality associated with the electricity prices. This effect is particularly evident in the strong price reductions verified during winters, corresponding to period of abundant electricity production from hydro and wind sources. There is also the possibility that this effect is strengthened by the growth of installed capacity, as presented in Table 1, especially in the case of wind energy. Regarding the CO_2 market, the price of emission permits decreased from 30€/ton in mid-2008 to a 5€/ton in mid-2013. Koch et al. (2014) and Fagiani et al. (2014) present as main causes for this collapse on CO_2 prices, the economic recession that followed the financial crisis of 2008 as well as the stimuli for renewable energies from public policies. Van den Bergh et al. (2013) also identify the growth of renewable energy penetration as the main cause of the CO_2 price decrease, along with the fact that the amount of emission permits issued during Phase III (2013–2020) appears to be excessive relative to actual needs.

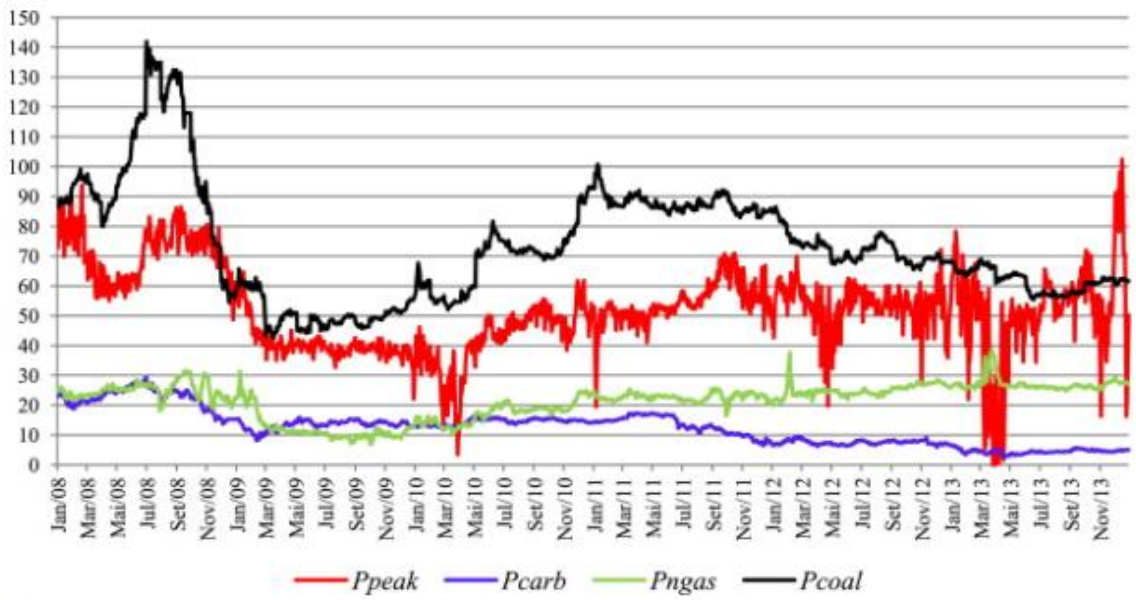

Fig. 1.

Electricity, carbon and fuel prices.

P_{peak} – electricity price (peak hours); P_{carb} – carbon (EUA) price; *Pngas* – natural gas price; P_{coal} – coal price.

4. Model description

It is becoming well known that dynamic interactions may be important in the formation of electricity prices. In understanding the interaction of electricity and input prices, there are complex relationships to consider. For instance, given the marginal technologies present in the Spanish electricity system, it would appear likely that coal and natural gas prices influence electricity prices and also EUA 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 arising 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 co-integrated 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 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 imposes 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 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 (1991). Assuming the existence of cointegration, the data generating process *Pt* 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 μt. One can write the *p-variate* process as.

$$P_t = \mu_t + A_1 P_{t-1} + A_2 P_{t-2} + \cdots + A_k P_{t-k} + \varepsilon_t.$$

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:

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

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

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 ($p \times r$) 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 hold all the time, however the deviation X_t is 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 by Harbo et al. (1998) and Pesaran et al. (2000) to include exogenous variables in the model. This is particularly useful in our case because it allows an adequate treatment of the renewable energy and temperature variables.

We formulate a general VECM specification as:

$$\Delta P_t = \alpha\beta P'_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta P_{t-1} + \theta \acute{R}_t + \Phi T_t + \mu_t + Sd_t + \varepsilon_t \qquad (3)$$

- Where P_t is a *(4 × 1)* 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. Terms α and β are a *(4 × r)* [5] 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 (4 × 4) matrix with the estimations of short-run parameters relating price changes lagged *i* periods.
- Where θ is a *(2 × r)* matrix of coefficients associated with the (2 × 1) vector R_t that represents the exogenous renewables variables [6]: $R_t = [Ind_t^{hydro}, Ind_t^{wind}]$ – Ind_t^{hydro} is the *Hydroelectric Producibility Index* and Ind_t^{wind} represents the *Wind Power Producibility Index*.
- Where Φ is a (4 × 2) matrix of coefficients associated with the (2 × 1) vector T_t that represents the exogenous temperatures variables: $T_t = [CDD_t, HDD_t]$ with *HDD* and *CDD* as defined previously.
- Where μ_t is a (*r* × 1) vector of constant [7] and ε_t is a (4 × 1) vector of innovations.
- Where d_t is a deterministic component containing centered seasonal dummy variables to capture the weakly and monthly seasonality.

In this study we test the hypothesis of a long-run relationship (or cointegration) between the price of the electricity, the price of carbon, and the prices of fuels (natural gas and coal), taking into account the amount of renewable electricity present in the market and the effect of the weather on electricity demand. According to our theory, as supported by the literature, we expect a positive relationship between the electricity price and the input prices (carbon and fuels), a negative sign for the coefficients representing renewable energy, and a positive sign for the coefficients representing temperature. Because the electricity price response to changes in CO_2 price may not be constant across time, we test our model for the three different load regimes (peak load, off-peak load, and base load).

5. Empirical results

5.1. Unit root and cointegration tests

We started our estimation procedure by testing the non-stationarity for all price series. 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 unit root for all specifications tested, according both the Augmented Dickey–Fuller Test (ADF test) and the Unit Root test with Breaks, which accounts for the possibility of level shift.

When testing for stationarity, the Kwiatkowski, Phillips, Schmidt and Shin Test (KPSS test), all series reject the null at a 1% significance level. On the contrary, we have evidence that the differenced series are stationary (ADF test and 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 tests						KPSS tests			Unit root tests with b		
Natural Logarithm of Prices – Levels									*Natural Log. of Price Levels*		
	Lag	Constant		Const&Trend		Lag	Constant	Const&Trend	Lag		Consta
		Stat.	p-value	Stat.	p-value		Stat.	Stat.			Stat.
Ppeak	13	−2.58	0.10	−2.53	0.31	8	1.96***	1.93***	*Ppeak*	13	−1.36
Pcarb	2	−1.09	0.72	−2.19	0.49	8	9.29***	1.12***	*Pcarb*	2	−0.61
Pngas	0	−2.14	0.23	−2.41	0.37	8	3.29***	2.02***	*Pngas*	0	−1.47
Pcoal	0	−1.36	0.60	−1.35	0.87	8	1.54***	1.58***	*Pcoal*	0	−1.35
Natural Logarithm of Prices – First Diferrences											
	Lag	Constant		No Constant		Lag	Constant		Lag		Const.
		Stat.	p-value	Stat.	p-value		Stat.				Stat.
ΔP^{peak}	12	−14.7	0.00	−14.7	0.00	8	0.03 –		*Ppeak*	13	−1.65
ΔP^{carb}	1	−26.0	0.00	−26.0	0.00	8	0.06 –		*Pcarb*	2	−1.80
ΔP^{ngas}	0	−36.8	0.00	−36.9	0.00	8	0.11 –		*Pngas*	0	−1.91
ΔP^{coal}	0	−33.7	0.00	−33.7	0.00	8	0.16 –		*Pcoal*	0	−1.34

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 the 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 by Johansen (1991). Since the VAR model contains exogenous variables, the Osterwald-Lenum (1992) and Johansen (1995) asymptotic critical values are no longer valid; we therefore used the asymptotic critical values provided by 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 within the cointegration space.

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

Table 4.
Cointegration tests.

H_o:			Trace test			λ_{max} – max Eigen Value test		
$r=$	p-$r=$	*Eigen values*	Statistics	Critical values	p-values	Statistics	Critical values	p-values
0	4	0.0963	174.49	91.59	0.00	127.65	41.57	0.00
1	3	0.0250	46.84	64.33	0.52	31.88	35.09	0.11
2	2	0.0092	14.96	40.85	0.98	11.59	28.31	0.93
3	1	0.0027	3.38	20.84	1.00	3.38	20.84	0.99

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 4 exogenous variables. *p* refers to the number of endogenous variables. *r* refers to the number of cointegrated vectors.

5.2. Estimation results for phase II of EU ETS (2008/2012)

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 [9] and they are all significant (at a 5% significance level for coal price and at 1% significance for all other variables) according to both the *t-test* and the *LR test* (Likelihood Ratio Test) as shown by Johansen (1995) [10]. Since the coefficients can be interpreted as price elasticities, a carbon price rise of 1% would, in equilibrium, be associated with an electricity price rise of 0.24%. In the same way, a natural gas (coal) price rise of 1% would be associated with an electricity price rise of 0.39% (0.19%).

Table 5.
VECM parameter estimates.

Cointegration Relationship				
Endogenous Variables				
	P_t^{peak}	P_t^{carb}	P_t^{ngas}	P_t^{coal}
	1.00	−0.24*** (0.04)	−0.39*** (0.07)	−0.19** (0.09)
Exogenous Variables + Deterministic Terms				
	Ind^hydro	*Ind^wind*	*Const.*	
	0.30*** (0.03)	0.28*** (0.07)	−1.80*** (0.21)	
Short Run Dynamics				
	ΔP_t^{peak}	ΔP_t^{carb}	ΔP_t^{ngas}	ΔP_t^{coal}
EC_{t-1}	−0.28***	–	–	–
ΔP_{t-1}^{peak}	−0.25***	0.01**	–	–
ΔP_{t-1}^{carb}	–	0.05*	0.11**	0.09***
ΔP_{t-1}^{ngas}	–	–	−0.05*	–
ΔP_{t-1}^{coal}	–	−0.12***	–	0.05*
Exogenous Variables + Seasonal Dummies				
CDD	0.005***	–	–	–
HDD	0.005***	–	–	–
Day of week	***	–	–	–
Month of year	***	–	**	*

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

This pass-through rate of the CO_2 price into electricity price of 24% 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, 70% in Aatola et al. (2013) for the French 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). Moreover, the sign and statistical significance of the associated coefficients for the renewables indexes are as expected (*Indhydro* e *Indwind*), reflecting the negative impact of the quantity of renewable energy on electricity prices and therefore confirming the results presented by Gelabert et al. (2011).

Analyzing the short-run dynamics of the model, especially for the equation of interest (ΔP_t^{peak}), we can see that the error correction term (EC_{t-1}) is strongly significant (1% level) and negative, meaning that the electricity price is adjusting to a long-run equilibrium, with a speed of adjustment of 0.28 (i.e., 28% of the disequilibrium in the long-run price is correct in one period). Considering the short-run parameters in the VAR, only the lagged electricity price is significant, suggesting that the price of electricity is essentially exogenous in the short run. There is also strong evidence that the weather variables are important for electricity price changes in the short run, having a positive impact when the demand of electricity reflects either heating (*HDD*) or cooling (*CDD*) purposes. It is also possible to verify from the statistical significance of the *dummy* variables that the model is correctly adjusted to seasonality, for both the day of the week and month of the year.

A weak long-run exogeneity test is performed (Juselius, 2006) for the null hypothesis that each of the series does not respond to the innovations or shocks in the cointegration space, (i.e., the series is unresponsive to deviations from the long-run relationships). This test is performed on α. According to the results reported in Table 6, at 1% 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 as expected since carbon, natural gas, and coal are globally traded commodities and thus may be driven more by forces outside the Spanish energy market. An exclusion test also is performed (Juselius, 2006) for the null hypothesis that a particular series is not in the cointegration space. This test is performed on β. As we can see, with the exception of coal price, all series reject the null at 1% significance, meaning that all coefficients are strongly significant. The presence of the coal price in the long-run relationship requires acceptance of a 10% significance level. Hence, there is strong evidence that all of the price series (carbon, gas, and coal prices) and the amount of renewable energy, both hydroelectric and wind power, are important to define the equilibrium vector; that is, all are essential to define the level to which electricity price is attracted over time. [11]

Table 6.
Exclusion and long-run or weak exogeneity tests.

	Exclusion Test		Exogeneity Test	
	LR stat.	p-value	LR stat.	p-value
P^{peak}	129.1	0.00	128.7	0.00
P^{carb}	28.6	0.00	0.2	0.65
P^{ngas}	23.0	0.00	0.2	0.63
P^{coal}	3.3	0.07	1.8	0.18
Ind^{hydro}	45.1	0.00		
Ind^{wind}	16.7	0.00		
const	47.1	0.00		

Notes: LR refers to Likelihood Ratio Test statistics.

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 7.
Diagnostic tests on residuals.

Diagnostic tests on residuals
- Serial Correlation [H_0: uncorrelated]
Breusch-Godfrey LM (Lagrange Multiplier) Test
AR (5), $\chi2$ (80) = 94.070 [0.135]
- Heterocedasticity [H_0: homokedastic]
Multivariate Conditional Heterocedasticity (ARCH) Test
VARCH (5), $\chi2$ (500) = 1202.97 [0.000]
- Normality (H_0: normal distributed)
Doornik–Hansen Test
Normality, $\chi2$ (8) = 168604.1 [0.000]

Notes: p-values in parentheses.

Table 8.
Residuals correlation matrix.

ΔP^{peak}	1	0.015	0.009	−0.018
ΔP^{carb}	–	1	0.097	−0.045
ΔP^{gas}	–	–	1	0.060
ΔP^{coal}	–	–	–	1

In Table 9 we report the results for the strategy implemented to consider significant differences in the pass-through rate of CO_2 price into electricity price across time. We estimated three alternative models defined according to electricity load regimes (peak load, off-peak load, and base load). As we can see, the coefficient associated with the carbon price for the three models is not significantly different, demonstrating that the impact of carbon on electricity prices is roughly the same through all periods of the day. Only the coefficients associated with the coal price and hydroelectric index present considerable differences for the *peak-hour* and *off-peak-hour* periods. The sensitivity of the electricity price to these variables is higher in periods of lower demand, which is consistent with the fact that these technologies have lower marginal costs.

Table 9.
Results for different regimes load.

Price of electricity: Peak load						
P_t^{peak}	P_t^{carb}	P_t^{gas}	P_t^{coal}	Ind^{hydro}	Ind^{wind}	Const.
1.000*** (0.00)	−0.241*** (0.04)	−0.391*** (0.07)	−0.186* (0.09)	0.297*** (0.03)	0.278*** (0.07)	−1.803*** (0.21)
EC_{t-1} = −0.28*** (0.02)						
Price of Electricity: off-peak load						
$P_t^{off-peak}$	P_t^{carb}	P_t^{gas}	P_t^{coal}	Ind^{hydro}	Ind^{wind}	Const.
1.000*** (0.00)	−0.245*** (0.06)	−0.394*** (0.10)	−0.235 - (0.13)	0.352*** (0.05)	0.265*** (0.09)	−1.378*** (0.30)
EC_{t-1} = −0.26*** 0.02						
Price of Electricity: base load						
P_t^{base}	P_t^{carb}	P_t^{gas}	P_t^{coal}	Ind^{hydro}	Ind^{wind}	Const.
1.000*** (0.00)	−0.254*** (0.04)	−0.409*** (0.07)	−0.172* (0.09)	0.322*** (0.03)	0.245*** (0.07)	−1.682*** (0.21)
EC_{t-1} = −0.28*** 0.02						

Notes: EC_{t-1} refers to the adjustment coefficients (α). Standard errors in parentheses. Likelihood Ratio (LR) Significance Test: *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

5.3. Estimation results for phase II and phase III of EU ETS (2008/2013)

Extending the analysis to Phase III of EU ETS will be important first, to understand if changes in the sector rules associated with the allocation of emission permits affect the influence CO_2 on the price of electricity[12] and second, to understand if the trend of falling CO_2 prices affects the sensitivity of electricity prices to the cost of CO_2 emissions. For this analysis, three periods were considered: a sub-period of Phase II, representing a period when the CO_2 price remained consistently above the 15€/ton level (January, 2008 to June, 2011); a period corresponding to the complete Phase II and whose results were previously analyzed (January, 2008 to December, 2012); and a period that included the first year of Phase III implementation (January, 2008 to December, 2013).

As presented in Table 10, the sensitivity of the electricity price to the CO_2 price has diminished over time. Throughout Phase II, the price elasticity of electricity relative to the price of CO_2 shifted from 0.37 to 0.25, when the CO_2 reached values below the 10€/ton level and when, including the first year of Phase III, the elasticity fell to 0.19. It is important to highlight that the coefficient associated with the CO_2 price for the period including Phase III is significant only at the 5% level. It can be concluded that a very low price for CO_2 over extended periods of time may result in lower electricity prices that inhibit the incentives for electricity producers to invest in emissions reduction or electricity consumers to invest in end-use efficiency.

Table 10.
Results for different periods of phase II and phase III of EU ETS.

Period: jan./2008_jun./2011 (part of phase II of EU ETS)						
P_t^{base}	P_t^{carb}	P_t^{gas}	P_t^{coal}	Ind^{hydro}	Ind^{wind}	$Const.$
1.000*** (0.00)	−0.365*** (0.11)	−0.392*** (0.09)	−0.130 - (0.13)	0.351*** (0.04)	0.288*** (0.09)	−1.655*** (0.26)
EC_{t-1} = −0.241*** (0.02)						
Period: jan./2008_dec./2012 (all Phase III of EU ETS)						
P_t^{base}	P_t^{carb}	P_t^{gas}	P_t^{coal}	Ind^{hydro}	Ind^{wind}	$Const.$
1.000*** (0.00)	−0.254*** (0.04)	−0.409*** (0.07)	−0.172* (0.09)	0.322*** (0.03)	0.245*** (0.07)	−1.682*** (0.21)
EC_{t-1} = −0.280*** (0.02)						
Period: jan./2008_dec./2013 (all Phase II + part of Phase III of EU ETS)						
P_t^{base}	P_t^{carb}	P_t^{gas}	P_t^{coal}	Ind^{hydro}	Ind^{wind}	$Const.$
1.000*** (0.00)	−0.187** (0.08)	−0.466*** (0.14)	−0.076 - (0.20)	0.392*** (0.06)	0.210 - (0.14)	−2.126*** (0.46)
EC_{t-1} = −0.304*** (0.02)						

Notes: EC_{t-1} refers to the adjustment coefficients (α). Standard errors in parentheses. Likelihood Ratio (LR) Significance Test: *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

6. Conclusion and policy implications

We analyzed the impact of CO_2 emission allowance prices on the Spanish electricity market using a cointegrated vector error correction model (VECM). 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 affecting the demand for electricity (i.e., weather variables) and the amount of renewable energy resources (hydroelectric and wind power) present in the market. The model was estimated using daily data, first for a period corresponding to whole Phase II of the EU ETS (2008–2012) and then including the first year of Phase III (2008–2013).

Taking into account the fuel prices (natural gas and coal) and produced renewable energy, we demonstrate that carbon price plays an important role in formulating the long-run equilibrium price of electricity. For the period corresponding to the Phase II, when the emissions allowances were allocated to power producers for free, we estimated an electricity price elasticity of 0.24, meaning that a 1% shock in carbon price translates to a 0.24% shock in electricity price in the long-run.

These empirical results are in line with studies concerning other European electricity markets, supporting the hypothesis that power producers during the second phase of EU ETS have passed the cost of freely allocated emission allowances through to electricity prices. It is possible to conclude that power producers' competitiveness would not have been affected if they had paid for the emissions allowances. Although a more definitive conclusion should account for the price elasticity of demand, which could be an interesting topic for future research, these results support changing the allocation rules for emissions allowances for the electricity sector from grandfathering to auctioning, as implemented by the European Commission for the Phase III of the EU ETS started at January 2013. However, estimating the model for different time lengths enables us to conclude that the sensitivity of electricity prices to the price of carbon emissions is also lower at lower carbon prices.

This study may be the first to provide empirical evidence of the impact of carbon price on electricity price during Phase III of EU ETS implementation. Our findings clearly make the case that the collapse of the CO_2 price weakens the link between the carbon market and the electricity market, consequently putting at risk the policy goals associated with carbon pricing. At low carbon prices, the incentives for electricity producers to reduce their emissions (through less carbon intensive production technologies), and the stimuli for consumers to cut their long-term consumption (through more end-use efficiency) will dissipate.

Various studies have demonstrated that the decrease in the carbon price is evident of the excess of emission permits held by economic agents (approximately 2.1 billion permits) associated with a decline in electricity demand (driven by the decrease in economic activity) as well as by the increase in the sector's use of renewable resources (Van den Bergh et al., 2013) and Koch et al., 2014). The findings from this research confirm the risk of carbon lock-in that the EU ETS faces (i.e., the domination of fossil-fuel-based technologies despite the greater dynamic efficiency of carbon-free alternatives). Our findings also support the need for action from regulatory policies that prevent extended period of reduced carbon prices. An example of this type of action was proposed by the European Commission, and approved by the European Parliament, in December 2013, delayed the emission permits auction foreseen for Phase III (a back-loading decision). Nonetheless, to ensure the efficacy of the system for delivering environmental goals, long-term structural policies are necessary.

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