# Carbon price drivers in the second phase of the EU ETS

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**Abstract**

This paper investigates the long-term and short-term determinants of the carbon price during the second phase of the European Union Emission Trading Scheme (EU ETS (2008-2012)). Assuming markets efficiency, I examine the extent to which the allowance price can be explained by marginal abatement costs. Specifically, I derive and estimate a structural model of allowance price while accounting for two structural breaks occurred on the carbon spot price series on October 2008 and September 2011. While the first break resulted mainly from the 2008 financial and economic crisis, the second break is probably caused by the economic downturn in late 2011. I find a significant long-run equilibrium between the carbon price, the price of gas and the economic activity. I find also that the short-run dynamics reflect adjustments in accord with convergence toward that long-run equilibrium. In addition to the long-term determinants, the short-term determinants of carbon price include the price of coal. I find evidence of a trade-off between gas and coal in electricity-generation in the short-run. I conclude that switching from coal toward gas is the abatement method of choice in the short-term.

**Keywords**: Carbon Emission Trading, Energy prices, Structural econometrics, structural breaks.
**JEL classification**: C14 C32 C51 G14 Q49 Q53 Q58

## 1 Introduction

By launching a new asset market, the EU ETS brings up new business development opportunities for market intermediaries and service providers. For market analysts, economists, risk management consultants, brokers and traders, determining carbon price fundamentals, understanding the behavior and the dynamics of emission allowance price, as well as the analysis of its impacts on the most polluting industries are of primary importance. Consequently, the number of empirical studies on the

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EU ETS and its impacts has exponentially increased. Among them, a large part deals with the impact of CO2 prices on electricity wholesale prices in various European markets to determine whether and to what extent the price of carbon is passed through electricity prices (Sijm et al, 2005 and 2006 ; Honkatukia et al, 2008 ; Kirat and Ahamada, 2011 ; Ahamada and Kirat, 2011, 2012a and 2012b). Another part adopts a financial approach to model the stochastic patterns and the volatility of the price of carbon-allowances mainly for risk management and forecasting purposes (Seifert et al, 2008 ; Benz and Trück, 2009 ; Chesney and Taschini, 2012).

There is also another facet of the literature that is closest to our issue and explicitly focuses on assessing the impact of widely accepted market fundamentals of the carbon price such as fuel prices, weather conditions and economic indicators (Mansanet-Bataller et al., 2007 ; Alberola et al., 2008 ; Bunn and Fezzi, 2008 ; Hintermann, 2010 ; Bredin and Muckley, 2011 ; Creti et al., 2012). Mansanet-Bataller et al. (2007) estimate the carbon price variations as a function of fuel price changes, weather indices, and several dummies accounting for largest price changes. They focus on the first year of the EU ETS and find that dummy variables capture most of the carbon price variations. The remaining are attributed to lagged variations in oil and gas prices and to the temperature in Germany. Hintermann (2010) criticizes the inclusion of oil price among the explanatory variables. He considers that the link between oil and carbon-allowance prices is not obvious. He argues that because of the little power generated using oil in Europe the switch from oil to gas is not likely to be the marginal abatement activity. Alberola et al. (2008) extend the study by Mansanet-Bataller et al. (2007) and include data through 2006. They also include additional explanatory variables of carbon price variations such as variations in electricity price and clean dark and clean spark spreads.[1] Unfortunately, while treated as exogenous these additional regressors appears to be strongly endogenous. In fact, Bunn and Fezzi (2008) use a vector error correction model with allowances, electricity and gas prices in the United Kingdom, and daily temperatures in London and seasonal dummies as exogenous variables. They carried out a structural analysis through imposing short-run identifying restrictions. They find that the UK gas price influences the allowance price, and that both gas and carbon prices help determine the electricity price. Unlike aforementioned studies which incorporate market fundamentals and specify the econometric models in an ad hoc way, Hintermann (2010) caries out the first analysis based on a market model. He estimates a short-term structural[2] model where changes in the carbon price are function of market fundamentals related to aggregate abatement such as coal and gas prices variations, daily equity-index returns, and weather variables. In the base specification he finds that carbon price

[1] The spark spread (dark spread) is the theoretical gross margin of a gas-fired (coal-fired) power plant from selling a unit of electricity, having bought the fuel required to produce this unit of electricity. The Clean spark spread (Clean dark spread) is the net revenue a generator makes from selling power, having bought gas (coal) and the required number of carbon allowances.

[2] There is a real risk of confusion in the use of the word structural because of the many uses to which it has been put by different authors. While many time series econometricians refer to structural to invoke the properties of constancy across regime schifts, theoricians employ this term to explicitly point out economic theories with microeconomic foundations. Structural is sometimes used to simply describe parameters or relations that have a direct economic interpretation without relying on strong microeconomic foundations as is the case here.

variations were mainly driven by gas price variations. When nonlinear terms are introduced, he finds that, after April 2006, changes in fuel prices, temperatures and precipitations help determine variations in the carbon price. The studies mentioned so far only cover the pilot phase of the EU ETS. The literature covering the pilot phase is abundant, while that which covers the second phase is rather scarce because it is a more recent phase. I am aware of two published papers that extend the analysis to phase II. Bredin and Muckley (2011) investigate the determinants of the price of carbon futures contracts during both phases of the EU ETS until the end of 2009. They use cointegration methodology to assess whether there are cointegration relationships between the price of carbon futures contracts, futures oil prices, clean dark and clean spark spreads, and indices of equity price and industrial production as proxies for the economic activity. They find evidence of cointegration in phase II but none in phase I. Creti et al. (2012) go beyond the analysis by Bredin and Muckley (2011) and include data through 2010. They estimate cointegration relationships between the carbon price, the price of oil, the switching price and an equity price index. They find cointegration over both phases and claim that the nature of the relationships has changed from phase II reflecting an increasing role of fundamentals.

While the aforementioned studies are valuable and useful contributions, most of them are not based on a formal model. Hintermann (2010) is the only article that relies on a market model, but it focuses only on short-run dynamics leaving aside the long-run analysis. Hence, the main contributions of this paper are twofold. Firstly, this is the first known study based on a convincing market model which considers a long-run equilibrium alongside a short-run dynamics. Secondly, the study uses a large dataset covering the whole second phase until 2012, and accounts for structural breaks in the carbon spot price series.

In this paper, I examine whether the allowance price in the second phase of the EU ETS is based on market fundamentals entering the marginal abatement cost function. I set up an economic model that considers both a long-term equilibrium and a short-term dynamic of allowance price. The equilibrium relationship specifies allowance price as a function of fuel prices and an indicator of the economic activity. The short-term dynamic specifies allowance price variations as a function of fuel price variations, changes in the economic performance index, and discrepancies from the equilibrium. I use various specifications of the marginal abatement cost function and show that the model in which fuel prices enter nonlinearly is the most adequate. I find that, unlike the coal price, the gas price and the economic activity drive the spot price of carbon-allowances in the long-run equilibrium. I show that the long-run relationship between the carbon spot price and the price of gas is non-linear and well represented by a quadratic function. I identify short-run determinants of the carbon price as being coal and gas prices and variations in the economic activity. I find also evidence that fuel switching from coal toward gas in electricity generation is the abatement method in the short-run.

The rest of the paper is organized as follows. Section 2 derives the allowance market model.

Section 3, organized in four subsections, details the steps of the econometric analysis. The first two subsections describe the data. The third subsection tests the basic assumption of the market model. The last subsection then presents the results and their interpretation. Last, Section 4 concludes.

## 2 The market model of allowances

In order to account for the long-run relationship between carbon price, energy prices, and economic activity, I extend a model proposed by Hintermann (2010)[3] which models the short-run determinants of emission permit prices over the first phase of the EU ETS. The model I propose goes further and accounts for the long-run determinants of emission permit prices alongside their short-run determinants over the second phase of the EU ETS. Let $BAU_{it}$ denote firm $i$'s random business-as-usual or counterfactual emissions (referring to emissions in the absence of carbon costs) in period $t$ with $t \in \{1, 2, ..., T\}$. Following Hintermann (2010), I assume that a common risk factor causes the stochastic volatility of business-as-usual emissions. Other uncertain factors are specific to each firm and cannot be correlated among firms. More specifically, the business-as-usual emissions of each firm are random variables subject to the randomness of the common risk factor $\Psi_t$ as follows:

$$BAU_{it}(\Psi_t) = E_{t-1}\left[BAU_{it}(\Psi_t)\right] + \beta_i(\Psi_t - E_{t-1}\left[\Psi_t\right]) + \varepsilon_{it} \tag{1}$$

where $\Psi_t$ is normally distributed, and $Cov(\Psi_t, \varepsilon_{it}) = 0$, $E[\varepsilon_{it}/\Psi_t] = 0$ for all $i$, and $E[\varepsilon_{it}\varepsilon_{jt}] = 0$ for all $i$ and $j$ with $i \neq j$. $\beta_i$ is the correlation coefficient multiplied by the standard deviations of $BAU$ divided by the standard deviation of $\Psi$. That is,

$$\beta_i = corr(BAU_{it}, \Psi_t) \times \frac{sdev(BAU_{it})}{sdev(\Psi_t)} = \frac{Cov(BAU_{it}, \Psi_t)}{Var(\Psi_t)}$$

this assumption introduces that firm $i$'s business-as-usual emissions in the current period are the sum of expected emissions and an adjustment term that is a function of shocks to the common risk factor $\Psi_t$, which contains exogenous variables that influence either demand or supply of emissions (the economic environment for instance).

Abatement is defined as the difference between firm $i$'s counterfactual emissions $BAU_{it}$ and actual emissions $AE_{it}$:

$$a_{it} = BAU_{it}(\Psi_t) - AE_{it} \tag{2}$$

Abatement has a cost defined by a firm's abatement cost function ($AC$) or its derivative, the marginal abatement cost ($MAC$) function. A well-known result in permit market theory is that each firm chooses a level of abatement such that its $MAC$ equals the permit price in every period, which

[3] This model by Hintermann is already an extension of a model proposed by Maeda (2004).

implicitly defines the optimal amount of abatement $a_{it}^*$:

$$P_t^{CO2} = MAC_{it}(a_{it}^*, F_t, BAU_{it}(\Psi_t)) \tag{3}$$

where $a_{it}^*$ is the firm $i$'s abatement that equalizes its marginal abatement cost with the market price of emission permits and $F_t$ refers to a vector of variables that determines the $MAC$ function. To clear the market, aggregate abatement has to equal the difference between aggregate $BAU$ emissions and the emissions cap $S$:

$$\sum_{k=1}^{T}\sum_{i=1}^{N} a_{ik}^* = \sum_{k=1}^{T}\sum_{i=1}^{N} BAU_{ik} - S \tag{4}$$

Because firms involved in the production of power and heat are dominant within the EU ETS, and because they may be able to abate emissions without either cutting output or building new plants (in contrast to the other sectors) I focus on emissions and abatement in this sector. I assume that the predominant method of abatement is a shift in the generation dispatch order away from coal towards gas, because the former is more than twice as emissions-intensive per unit of output than the latter. Fuel switching is generally considered to be abatement method of choice in the EU ETS given that there is not enough time between the formalization of phase III and the end of phase II for firms to alter production technology significantly. This means that in addition to $BAU$ emissions, abatement costs in the EU ETS depend on gas and coal prices and on capacity for production shifts.[4]

Throughout this paper I assume the presence of uncertainties in the firm's abatement cost and marginal abatement cost functions ($AC_{it}$ and $MAC_{it}$). Firms do not know exactly their (marginal) abatement cost functions. These uncertainties may be due to expectations of some variables which drive the (marginal) cost of abatement. In addition to uncertainties on $BAU$ emissions, it is well-known that price variables (gas and coal prices here) are in general functions of expectations formed by agents from their past experiences and new information that they acquire over time. This slightly modifies (3) and yields

$$P_t^{CO2} = E\left[MAC_{it}(a_{it}^*, F_t, BAU_{it}(\Psi_t))\right] \tag{5}$$

or,

$$P_t^{CO2} = MAC_{it}(a_{it}^*, P_t^{gas}, P_t^{coal}, BAU_{it}(\Psi_t)) + e_{it} \tag{6}$$

equation (6) can be considered as a long-term equilibrium relationship with $e_{it}$ the deviation from that equilibrium. I assume that aggregate abatement cost functions are continuous and quadratic in abatement over the range where fuel switching is feasible as in Hintermann (2010). The market's

[4]Unlike fossil fuels, renewables are excluded here from the set of determinants of the marginal abatement cost of electricity producers. The main reason is that fossil fuels are more flexible than renewables in power generation. Indeed, unlike electricity generated from fossil fuels, random electricity production depending on weather conditions (solar, wind) does not satisfy electricity demand instantaneously.

abatement cost ($AC$) function can be written as:

$$AC(\sum_{i=1}^{N} a_{it}, P_t^{gas}, P_t^{coal}) = b_{1t} \sum_{i=1}^{N} a_{it} + \frac{b_2}{2} \left( \sum_{i=1}^{N} a_{it} \right)^2$$

where $P_t^{gas}$ and $P_t^{coal}$ refer to the prices of gas and coal, respectively. The resulting marginal abatement cost ($MAC$) function is linear and is reminiscent of that used by Schennach (2000):

$$MAC(\sum_{i=1}^{N} a_{it}, P_t^{gas}, P_t^{coal}) = b_{1t} + b_2 \sum_{i=1}^{N} a_{it} \tag{7}$$

where the constant slope $b_2 > 0$ ensures increasing marginal abatement costs and $b_{1t}$ is allowed to be time-dependant to account for shifts in marginal abatement costs arising from changes in electricity-generation technologies. Thus, I model $b_{1t}$ as a function of gas and coal prices such as $b_{1t} = f(P_t^{gas}, P_t^{coal})$, where $f$ represents the long-run relationship between the marginal abatement cost and energy prices. I first specify $f$ as a linear function such as:

$$b_{1t} = f(P_t^{gas}, P_t^{coal}) = \lambda_1 P_t^{gas} + \lambda_2 P_t^{coal} \tag{8}$$

Since electricity producers make complex calculations of production costs of different technologies while ensuring that production follows real-time demand, one can expect that the relationship between carbon, gas and coal prices is nonlinear. The trade-off between gas and coal in producing electricity requires introducing at least an interaction term and at most squared terms. In all case, one can test for the most suitable specification nested into the following more general specification:

$$b_{1t} = f(P_t^{gas}, P_t^{coal}) = \lambda_1 P_t^{gas} + \lambda_2 P_t^{coal} + \lambda_3 (P_t^{gas})^2 + \lambda_4 (P_t^{coal})^2 + \lambda_5 (P_t^{gas} P_t^{coal}) \tag{9}$$

obviously, the intermediate specification which includes an interaction term but excludes squared terms corresponds to specification (9) with the restrictions $\lambda_3 = \lambda_4 = 0$. This gives

$$b_{1t} = f(P_t^{gas}, P_t^{coal}) = \lambda_1 P_t^{gas} + \lambda_2 P_t^{coal} + \lambda_5 (P_t^{gas} P_t^{coal}) \tag{10}$$

In equilibrium, allowance demand must equal supply and the $E[MAC]$ has to equal the allowance price $P_t^{CO2}$. Recalling equation (6) where $e_t$ denotes a deviation from the equilibrium, this gives:

$$P_t^{CO2} = b_{1t} + b_2 \sum_{i=1}^{N} a_{it} + e_t \tag{11}$$

or,

$$\sum_{i=1}^{N} a_{it} = \frac{1}{b_2} \left( P_t^{CO2} - b_{1t} - e_t \right) \tag{12}$$

Substituting (12) in (4) yields:

$$\frac{1}{b_2}\sum_{t=1}^{T}\left(P_t^{CO2}-b_{1t}-e_t\right)=\sum_{t=1}^{T}\sum_{i=1}^{N}BAU_{it}(\Psi_t)-S \tag{13}$$

I now take expectations at time $t$, subtract them from (13), and simplify (entries for periods before $t$ cancel out because their ex-post expectations is the same as their realization):

$$\begin{aligned}\sum_{k=t+1}^{T}\left(P_k^{CO2}-E_t\left[P_k^{CO2}\right]\right) &= \sum_{k=t+1}^{T}\left(b_{1k}-E_t\left[b_{1k}\right]\right)\\ &+b_2\sum_{k=t+1}^{T}\sum_{i=1}^{N}\left(BAU_{ik}(\Psi_k)-E_t\left[BAU_{ik}(\Psi_k)\right]\right)\\ &+\sum_{k=t+1}^{T}\left(e_k-E_t\left[e_k\right]\right)\end{aligned} \tag{14}$$

Knowing that $E_t\left[e_k\right]=0$ and $E_t\left[E_{k-1}(\Psi_k)\right]=E_t(\Psi_k)$ if $k>t$, substituting (1) and dividing by $N$ gives

$$\begin{aligned}\frac{1}{N}\sum_{k=t+1}^{T}\left(P_k^{CO2}-E_t\left[P_k^{CO2}\right]\right) &= \frac{1}{N}\sum_{k=t+1}^{T}\left(b_{1k}-E_t\left[b_{1k}\right]\right)\\ &+\frac{b_2}{N}\sum_{k=t+1}^{T}\sum_{i=1}^{N}\beta_i\left(\Psi_k-E_{k-1}\left[\Psi_k\right]\right)\\ &+\frac{b_2}{N}\sum_{k=t+1}^{T}\sum_{i=1}^{N}\varepsilon_{ik}+\frac{1}{N}\sum_{k=t+1}^{T}e_k\end{aligned} \tag{15}$$

Provided that the error $\varepsilon_{ik}$ is stationary, the mean and variance of the term $\frac{b_2}{N}\sum\limits_{k=t+1}^{T}\sum\limits_{i=1}^{N}\varepsilon_{ik}$ go to zero as $N$ goes to infinity. The intuition behind this is that uncorrelated firm-specific shocks cancel each other out in a large market, i.e., only shocks that affect all firms simultaneously have an impact on $BAU$ emissions (and thus on marginal abatement costs). By setting $\widetilde{\beta}=\frac{1}{N}\sum\limits_{i=1}^{N}\beta_i$ and multiplying by $N$, I can simplify to

$$\begin{aligned}\sum_{k=t+1}^{T}\left(P_k^{CO2}-E_t\left[P_k^{CO2}\right]\right) &= \sum_{k=t+1}^{T}\left(b_{1k}-E_t\left[b_{1k}\right]\right)\\ &+b_2N\widetilde{\beta}\sum_{k=t+1}^{T}\left(\Psi_k-E_{k-1}\left[\Psi_k\right]\right)+\sum_{k=t+1}^{T}e_k\end{aligned} \tag{16}$$

I assume that markets are efficient (prices include all the available information and thus incorporate changes in underlying fundamentals fully and immediately). This imply that price has the Markov property and therefore that $E_t\left[P_{t+1}\right] = (1+r)P_t \equiv \rho P_t$ where $r$ is the interest rate and $P_t$ refers to any price. This applies to all the variables entering the model as they are nonstationary. For $t << T$, equation (16) can be solved recursively[5] to

$$P_t^{CO2} - \rho P_{t-1}^{CO2} = b_{1t} - \rho b_{t-1} + b_2 N\widetilde{\beta}\left[\Psi_t - \rho\Psi_{t-1}\right] + e_t \tag{17}$$

The day-to-day discount rate is close to zero then $\rho \approx 1$. Replacing $\rho = 1$ in (17) yields:

$$\Delta P_t^{CO2} = \Delta b_{1t} + b_2 N\widetilde{\beta}\Delta\Psi_t + e_t \tag{18}$$

where $\Delta$ refers to the first-difference operator and $\Psi_t$ includes factors that determines $BAU$ emissions. I choose to omit weather variables although there is a huge empirical literature which considers them as determinants of carbon prices. The reasons are twofold: i) the impact of weather variables on carbon prices is indirect and probably nonlinear since it is captured by sudden changes in energy demand (Creti et al., 2012) and ii) the geographic extent of Europe makes it difficult to build aggregated climate variables that would reflect the climatic differences between different territories and could substantially change the overall energy demand. So I only include proxy variables for the overall economic activity within the EU in $\Psi_t$.[6]

I assume that $e_t$ is stationary (the relevance of this assumption can be checked later using cointegration tests), then I can rewrite it in an autoregressive way up to order $p$ as follows:

$$e_t = \sum_{i=1}^{p} \alpha_i e_{t-i} + v_t \; where \; v_t \; is \; a \; white \; noise \; and \; |\alpha_i| < 1$$

assuming that $p = 1$ ($e_t \sim AR(1)$) and substituting in (18) yields

$$\Delta P_t^{CO2} = \Delta b_{1t} + b_2 N\widetilde{\beta}\Delta\Psi_t + \alpha_1 e_{t-1} + v_t \tag{19}$$

where $\alpha_1 < 0$ represents the return toward equilibrium and $e_{t-1} = P_{t-1}^{CO2} - (b_{1t-1} + b_2 N\widetilde{\beta}\Psi_{t-1})$ a misalignment or a deviation from the long-run relationship at $t-1$. The model to be estimated includes both short-term and long-term equations. This model is also reminiscent of error correction models:

[5] See the appendix for detailed resolution.

[6] $\Psi_t$ includes factors that determine either demand or supply of counterfactual emissions. On the supply side, I do not need to include fossil fuel prices as they are already included in the abatement cost function. On the demand side, economic activity determines emissions so I include a stock market index as a proxy for the overall economic activity. Weather variables can also impact on the demand of business-as-usual emissions but I exclude such variables for the reasons mentioned above.

$$
\begin{cases} \Delta P_t^{CO2} = \alpha_1 e_{t-1} + \Delta b_{1t} + b_2 N \widetilde{\beta} \Delta \Psi_t + v_t \\ P_t^{CO2} = b_{1t} + b_2 N \widetilde{\beta} \Psi_t + e_t \end{cases} \tag{20}
$$

Following the general-to-specific approach, I substitute successively (9), and different nested models within (9) in (20). Replacing the equity price index $Eurex_t$ in $\Psi_t$ yields the following general model:

$$
\begin{cases} P_t^{CO2} = \lambda_1 P_t^{gas} + \lambda_2 P_t^{coal} + \lambda_3 (P_t^{gas})^2 + \lambda_4 (P_t^{coal})^2 + \lambda_5 (P_t^{gas} P_t^{coal}) \\ \qquad + \lambda_6 Eurex_t + e_t \\ \\ \Delta P_t^{CO2} = \alpha_1 e_{t-1} + \beta_1 \Delta P_t^{gas} + \beta_2 \Delta P_t^{coal} + \beta_3 \Delta (P_t^{gas})^2 + \beta_4 \Delta (P_t^{coal})^2 \\ \qquad + \beta_5 \Delta (P_t^{gas} P_t^{coal}) + \beta_6 \Delta Eurex_t + v_t \end{cases} \tag{21}
$$

which embeds various restricted models including the ones modeling $f$ as in (8) and (10). Models from (20) considering the specification of $b_{1t}$ as in (8) and (10) are, respectively, the followings:

$$
\begin{cases} P_t^{CO2} = \lambda_1 P_t^{gas} + \lambda_2 P_t^{coal} + \lambda_6 Eurex_t + e_t \\ \\ \Delta P_t^{CO2} = \alpha_1 e_{t-1} + \beta_1 \Delta P_t^{gas} + \beta_2 \Delta P_t^{coal} + \beta_6 \Delta Eurex_t + v_t \end{cases} \tag{22}
$$

$$
\begin{cases} P_t^{CO2} = \lambda_1 P_t^{gas} + \lambda_2 P_t^{coal} + \lambda_5 (P_t^{gas} P_t^{coal}) + \lambda_6 Eurex_t + e_t \\ \\ \Delta P_t^{CO2} = \alpha_1 e_{t-1} + \beta_1 \Delta P_t^{gas} + \beta_2 \Delta P_t^{coal} + \beta_5 \Delta (P_t^{gas} P_t^{coal}) \\ \qquad + \beta_6 \Delta Eurex_t + v_t \end{cases} \tag{23}
$$

# 3 Econometric analysis

## 3.1 Data

I consider data of weekday frequency on the period February 26th, 2008[7] - February 24th, 2012. Due to its liquidity, the carbon spot price comes from the Bluenext environmental trading exchange expressed in € per ton. With respect to energy markets, I appeal to the following price series taken from Datastream and expressed in € per Mwh: i) the gas price of the month-ahead future contract traded on ICE exchange which is the leading market place for trading gas in Europe ; and ii) the coal price of the month-ahead future contract API2 CIF ARA traded on the European Energy Exchange market. These series being initially expressed in GBP per therm for gas and USD per metric tonne for coal, they have been converted into € per Mwh using daily exchange rate data available from

[7]The launch of Phase 2 emission allowance spot transaction on BlueNext was held on February 26th, 2008.

the European Central Bank website and energy conversion factors of $1 therm = 0.02931\ Mwh$ for gas and $1 ton \simeq 7.7\ Mwh$ for coal. I use European equity futures indexes to proxy for overall economic performance in the EU. In addition to the fact that these variables reflect financial and economic conditions expectations at the daily frequency, they allow considering the EUA as a financial asset and control for the 2008 financial crisis and the recent economic downturn of 2011, at the same time providing daily data (see Creti et al., 2012). Our retained equity variables extracted from Datastream are: i) the Dow Jones Euro Stoxx 50, which is Europe's leading stock index for futures contracts ; and ii) the Financial Times Stock Exchange (FTSE) Eurotop 100, which is a tradable index representing the 100 most highly capitalized blue chip companies in Europe. Our final sample consists of 1044 observations, the main characteristics of which are described below.

## 3.2 Descriptive analysis

Table 1 displays the summary statistics of carbon price, energy prices and equity indices. Figure 1 shows the carbon spot price series over the period from February 26th, 2008 until February 24th, 2012.

Table 1: Summary statistics

| Variable | Mean | Standard Deviation | Minimum | Maximum |
|---|---|---|---|---|
| Carbon spot price (€/ton) | 15.11 | 4.61 | 6.22 | 28.73 |
| Gas price (€/Mwh) | 24.74 | 7.53 | 9.30 | 43.46 |
| Coal price (€/Mwh) | 9.88 | 2.84 | 5.62 | 18.44 |
| Euro Stoxx 50 Index | 2467.80 | 318.65 | 1614.75 | 3308.61 |
| Eurotop 100 Index | 2168.55 | 280.90 | 1411.65 | 2879.49 |

The spot price of carbon fluctuated in the range of 20 to 30 € per ton from February 2008 until October 2008, peaking at over 28 € on July 1, 2008. From October 2008, the price of CO2 emissions fell below 20 € and declined to go below 8 € in February 2009. Then it rebounded to oscillate around 13 € - 14 €, reaching even 16 € in May 2011. Since June 2011, the carbon spot price initiated a decline towards 6 € at the end of the period. The sharp drops in carbon spot price initiated in October 2008 and June 2011 give a visual feeling of significant breaks in the carbon spot price series. Following Kirat and Ahamada (2011), I thus apply unit-root tests with structural breaks to detect the break dates in carbon spot prices. I apply successively the unit root test with a double change in the mean pioneered by Clemente Montanès and Reyes (1998) and the unit root test with a single change in the mean pioneered by Perron and Vogelsang (1992).[8] These tests are based on the same principle, where the break dates are endogenous. Each test encompasses two procedures, according to whether the series is detrended or not before performing the unit root test. The procedure consisting in applying

[8] See the Appendices for more details on these tests. To properly interpret the results of stationarity tests, the test procedure is to start with the test by Clemente Montanès Reyes. When this one accepts two dates of breaks, we stop and proceed to the interpretation of the unit-root test results. Otherwise we carry out the test by Perron-Vogelsang. The results of this test will be retained if the structural break turned out significant.

a filter before the test is called *AO* (Additive Outlier) and captures sudden changes in the series. That which detrends and performs the test at the same time is called *IO* (Innovational Outlier) and captures incremental changes in the mean of the series. The test findings regarding break dates are summarized in Figure 2.[9]

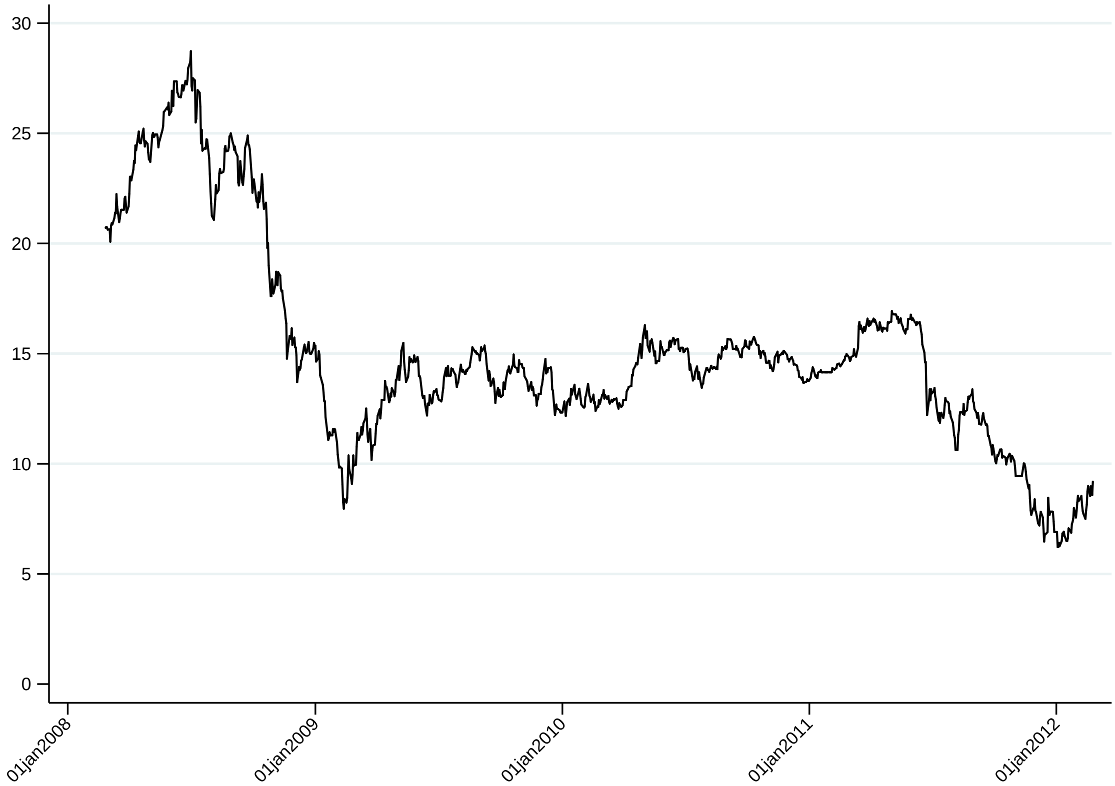


Figure 1: Carbon spot prices.

The test applied to the logarithm of the emission allowances spot price series suggests two structural breaks. The *IO* (*AO*) procedure puts these at October 13th, 2008 (November 21th, 2008) and September 14th, 2011 (November 28th, 2011). The first date(s) corresponds to the sharp drop in the price of carbon, which fell to below 15 € per ton. The emission permit loses over a half of its value in less than five months. This collapse in the carbon spot price is due to a low demand of emission permits, which in turn can be attributed to several factors. Firstly, the financial crisis and the declining global equity prices followed by the economic crisis caused a reduced economic activity of electricity producers and the major emitters of the industrial sector, which was inevitably followed by a drop in real emissions. Emissions of greenhouse gases from European Union businesses participating in the EU ETS fell by 11.6% in 2009 compared with 2008. Secondly, the low level of gas prices throughout 2009 made it much more attractive than coal in power generation. The second date corresponds to a

[9] See also Table 6 in the appendix for unit-root test results.

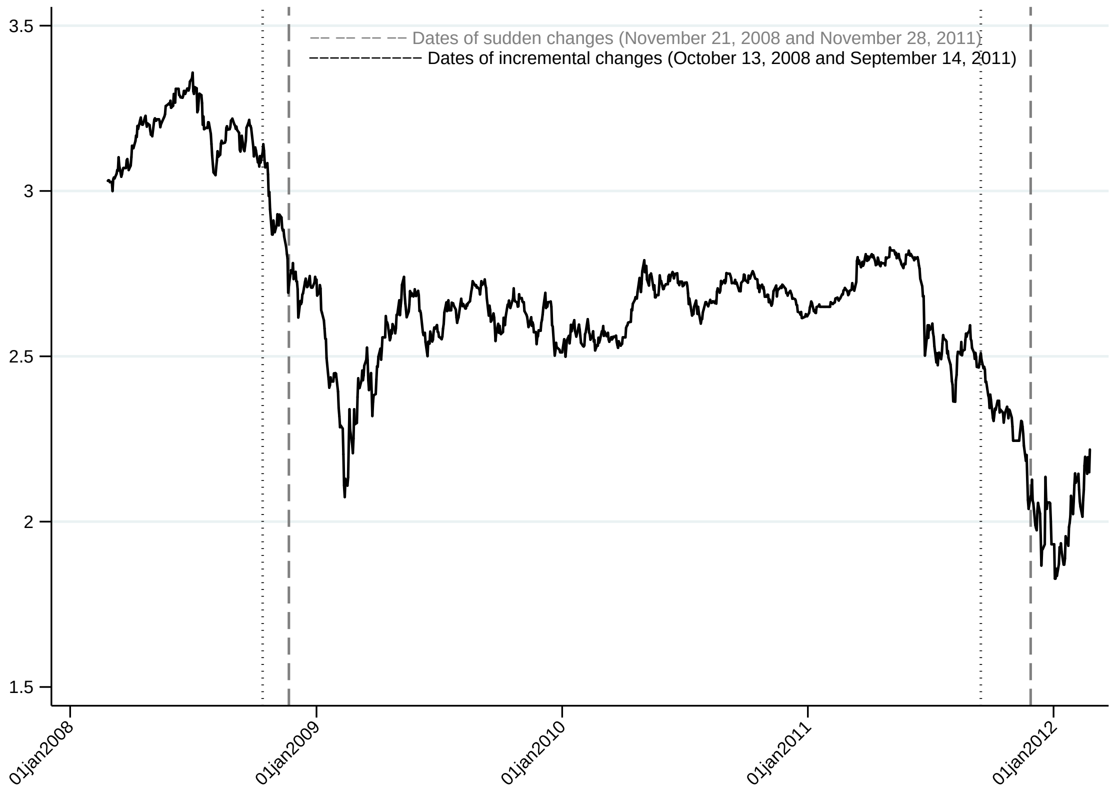


Figure 2: Dates of structural breaks in carbon spot price (in logs)

significant decline in the carbon spot price, which fell to below 7 € per ton in January 2012. Perhaps the economic downturn in late 2011 lowered the demand for emission-allowances. Despite an annual economic growth in Europe of 1.5% in 2011 compared to 2010, there was a decreased economic activity at the end of the year with a recession of 0.3% in the fourth quarter compared with the third. Consequently, the total verified emissions fell by 5.5% in 2011 compared with 2010.

### 3.3 Unit-root and cointegration tests

Before estimating the carbon price model, I use cointegration methodology to check whether $e_t$ is indeed stationary, especially since the model relies heavily on this assumption. Foremost, I pretest all variables entering the potential long-run relationship in (21) to assess their order of integration. According to the standard unit-root tests (ADF, PP, KPSS),[10] all variables are $I(1)$. Then, I estimate the following long-term equation derived from (21):

$$\begin{aligned} P_t^{CO2} &= \lambda_0 + \lambda_1 P_t^{gas} + \lambda_2 P_t^{coal} + \lambda_3 (P_t^{gas})^2 + \lambda_4 (P_t^{coal})^2 + \lambda_5 (P_t^{gas} P_t^{coal}) + \lambda_6 Eurex_t \\ &\quad + \omega_1 Break_{1t} + \omega_2 Break_{2t} + e_t \end{aligned} \tag{24}$$

where $P_t^y$ is the logarithm of the price of commodity $y$ in period $t$ and $Eurex_t$ the equity price index in logarithmic term.[11] Importantly, $Break_{1t}$ and $Break_{2t}$ are two dummy variables included to account for breaks occurred on the carbon spot price. They were built on the basis of the break dates detected using the $IO$ test-procedure.[12] At this stage, I proceed to Johansen's (1988, 1991) cointegration tests to assess whether equation (24) can be considered as an equilibrium relationship. Table 2 reports the results of the Johansen's trace and maximum eigenvalue tests. Both tests reject the null of no cointegration at conventional significance levels. Although the Johansen's tests did find cointegration, I carried out residual-based cointegration tests (Engle and Granger, 1987, and Phillips and Ouliaris, 1990) for robustness check purposes. Given the structural breaks occurred on the carbon spot price series, I also implemented cointegration tests robust to such breaks. Table 3 reports the results of the Johansen's trace test in the presence of two structural breaks proposed by Johansen et al. (2000). Fortunately, all these tests led to similar conclusions. The next subsection interprets the estimation results.

### 3.4 Results and interpretation

The results in Tables 4 and 5 refer to the estimated long-term equilibrium of the spot price of carbon and its short-term dynamics, respectively, over the period from February 26th 2008 to February

[10] All results are available upon request to the author.

[11] One can use either the Dow Jones Euro Stoxx 50 or the FTSE Eurotop 100 indices to proxy economic activity as both lead to similar results.

[12] Against model selection creteria and goodness-of-fit measures, the model that considers break dates detected using the AO procedure is less suitable.

Table 2: Results of Johansen's cointegration tests (p-value)

| Null hypothesis | Trace test | Maximum eigenvalue test |
|---|---|---|
| None | 0.002*** | 0.028** |
| At most 1 | 0.056 | 0.357 |
| At most 2 | 0.134 | 0.415 |
| At most 3 | 0.245 | 0.456 |
| At most 4 | 0.363 | 0.544 |
| At most 5 | 0.377 | 0.467 |
| At most 6 | 0.193 | 0.193 |

Note: *** and ** refer respectively to rejection of the null hypothesis at the 1% and 5% significance levels.

Table 3: Results of Johansen's cointegration tests with two structural breaks

| Null hypothesis | Trace statistic | Critical value (1%) | Critical value (5%) | P-value |
|---|---|---|---|---|
| None | 182.46 | 177.49 | 165.88 | 0.004*** |
| At most 1 | 131.73 | 141.23 | 130.83 | 0.044** |
| At most 2 | 94.07 | 108.84 | 99.65 | 0.113 |
| At most 3 | 59.27 | 80.43 | 72.45 | 0.343 |
| At most 4 | 33.27 | 56.08 | 49.29 | 0.600 |
| At most 5 | 15.08 | 35.61 | 30.06 | 0.772 |
| At most 6 | 4.67 | 19.22 | 14.83 | 0.767 |

Note: *** and ** refer respectively to rejection of the null hypothesis at the 1% and 5% significance levels. The critical values are tabulated by Giles and Godwin (2012). They also provide code that generates the corresponding p-values.

24th 2012. The estimation methodology uses a two-step procedure. I first focus on the equilibrium relationship and then consider the short term dynamics.

Estimation results of equation (24), which I denote by (A), are reported in Table 4. This also contains the estimation results of various equations embedded in (24), reflecting different specifications of $b_{1t}$. According to cointegration test results, these equations reflect different long-term equilibriums between carbon price, fuel prices and the economic activity. The only difference lies in how to model $b_{1t}$. Hence, in order to select the most apt model for the carbon spot price I adopt the general-to-specific approach to test the validity of restrictions leading to each submodel. I begin with the extremely general model in (24) and pare it down by testing various coefficient restrictions. I denote by (B) the equation from (A) where restrictions are $\lambda_3 = \lambda_4 = 0$. Equation (B) thus refers to the corresponding long-run equation in model (23). I also denote by (C) the equation from (A) where restrictions are $\lambda_3 = \lambda_4 = \lambda_5 = 0$. Equation (C) refers to the corresponding long-run equation in model (22). Insofar I am facing exogenous RHS variables, consistency of standard errors requires only uncorrelated errors. Accordingly, I correct the standard errors of the estimated coefficients using the Newey and West (1987)'s heteroskedasticity and autocorrelation consistent covariance estimator. However, for robustness purposes, I use likelihood ratio tests to assess the validity of the above restrictions. These are reported in the last row of Table 4 and clearly conclude to the rejection of equations (B) and (C). Moreover, all goodness-of-fit measures select equation (A) over equations (B) and (C). This means that among the three specifications of $b_{1t}$ considered here, only specification (9) is acceptable. Estimation results of equations (C) and (B) are given to illustrate their irrelevance.

I re-estimate equation (A) excluding the statistically insignificant variables to obtain equation (A'). So I focus only on interpreting the estimated coefficients of equation (A) and (A') displayed in the rightmost columns of Table 4. Fortunately, these estimation results are practically the same.

Table 4: Estimation results of the long-run relationships

| Equation | (C) | (B) | (A) | (A') |
|---|---|---|---|---|
| $P_t^{gas}$ | 0.062* | -1.092*** | -2.757*** | -2.760*** |
| | (0.034) | (0.159) | (0.296) | (0.293) |
| $(P_t^{gas})^2$ | | | 0.517*** | 0.474*** |
| | | | (0.103) | (0.049) |
| $P_t^{coal}$ | 0.088** | -1.854*** | -0.053 | |
| | (0.044) | (0.275) | (0.363) | |
| $(P_t^{coal})^2$ | | | 0.120 | |
| | | | (0.133) | |
| $P_t^{gas} P_t^{coal}$ | | 0.587*** | -0.136 | |
| | | (0.081) | (0.222) | |
| $Eurex_t$ | 0.287*** | 0.439*** | 0.447*** | 0.459*** |
| | (0.064) | (0.066) | (0.073) | (0.056) |
| $Break1$ | -0.403*** | -0.312*** | -0.320*** | -0.337*** |
| | (0.015) | (0.020) | (0.020) | (0.016) |
| $Break2$ | -0.530*** | -0.539*** | -0.542*** | -0.543*** |
| | (0.026) | (0.024) | (0.024) | (0.024) |
| $Cons$ | 0.437 | 2.960*** | 3.486*** | 3.360*** |
| | (0.489) | (0.487) | (0.529) | (0.498) |
| $Likelihood$ | 741.47 | 795.37 | 823.47 | 820.85 |
| $R-squared$ | 0.8408 | 0.8564 | 0.8640 | 0.8633 |
| $AIC$ | -1470.94 | -1576.74 | -1628.95 | -1629.70 |
| $BIC$ | -1441.23 | -1542.09 | -1584.39 | -1599.99 |
| LR tests | $\chi^2_{(3)}$= 164.01 [0.00] | $\chi^2_{(2)}$= 56.21 [0.00] | | |

Note: Standard errors based on the Newey and West (1987)'s heteroskedasticity and autocorrelation consistent covariance estimator are in (); * ** and *** refer respectively to the 10%, 5% and 1% significance levels of estimated coefficients; P-values of LR tests are in [ ].

The estimated coefficient on the economic activity is positive and highly significant. All else equal, a 1% higher economic activity leads to a rise of 0.459% in the carbon spot price in the long-run equilibrium. The estimated coefficients on dummy variables are negative and highly significant: the unconditional mean of the log carbon price decreased, respectively, by 0.337 and 0.910 after the successive breaks compared to the period before. Focusing on energy prices, the results show that the price of gas, unlike that of coal, determines the carbon spot price in the long-run equilibrium. This result is consistent with long-term strategies favoring cleaner technologies. The relationship between the carbon spot price and the gas price is actually U-shaped. The long-run elasticity of the carbon spot price relative to the gas price vary linearly across the whole gas price range. This elasticity is negative for low gas prices and becomes positive from a gas price threshold of 14.35 €$/Mwh$. Below the threshold of 14.35 €$/Mwh$, gas prices impact negatively the carbon spot price. This occurred from April 2009 to September 2009. Unfortunately, the negative elasticity here seems counter-intuitive. Indeed, assuming that the market model presented here is correct, this elasticity should be positive all the time since higher gas prices result in higher abatement costs in electricity-generation. Thus the efficient market model is suitable when the gas price exceeds the threshold. It is much less so when the gas price is below the threshold. This is perhaps linked to market power of electricity producers on the carbon market. In this regard, Hintermann (2010) highlights that large power producers exhibit the greatest potential for market power in the EU ETS. So, it is possible that below a specific gas price threshold (here 14.35 $€/Mwh$) the abatement cost of dominant firms becomes negligible, given the free allocation of emission allowances. These dominant firms then inflate the carbon price so as to maximize their own profits. This is consistent with the findings in previous papers concerning the possibility of strategic behaviours of electricity producers that lead to market manipulation. Hintermann (2010) highlights that even net permit demanders such as power generators can find it profitable to inflate the price of emission permits in some circumstances. This is the case if the free allowance allocation exceeds a specific threshold that is a function of cost throughput and firms' relative emission intensities.

Following Creti et al. (2012), I derive the equilibrium carbon price from the long-run relationship (A) to analyze whether the observed carbon price is at its equilibrium or departs from it. Figure 3 displays the observed and equilibrium price and shows that, globally, the adjustment between observed and forecasted values is quite good. Figure 4 reports the gap between both series interpreted as a misalignment (the relative difference between the observed price and its equilibrium value). It suggests that persistent disequilibriums (shocks) occur. Perhaps agents react to a greater extent downstream to the information from the carbon market. This is possible because of the distinction between the short-run daily carbon market and the long-run annual compliance to which market participants commit themselves.

I will now turn to the estimation results of the short-run equations. The results in Table 5 refer to the estimated short-run dynamics of the spot carbon price as specified in models (22), (23) and (21) reflecting the different specifications of $b_{1t}$. I denote by (a) the following short-run equation from the more general model (21):

$$\begin{cases} \Delta P_t^{CO2} = \alpha_0 + \alpha_1 e_{t-1} + \beta_1 \Delta P_t^{gas} + \beta_2 \Delta P_t^{coal} + \beta_3 \Delta (P_t^{gas})^2 + \beta_4 \Delta (P_t^{coal})^2 \\ \qquad +\beta_5 \Delta (P_t^{gas} P_t^{coal}) \ + \beta_6 \Delta Eurex_t + v_t \qquad v_t \ \sim N(0, \sigma_t^2) \\ \sigma_t^2 \ = \gamma_0 + \ \gamma_1 v_{t-1}^2 + \gamma_2 \sigma_{t-1}^2 \end{cases}$$

where GARCH effects, a very common form of heteroskedasticity in high-frequency time series, are modelled alongside the mean equation. In fact, ARCH tests on the residuals $v_t$ of preliminary regressions reject the null hypothesis of no ARCH effects. $e_{t-1}$ refers to the deviation from the equilibrium

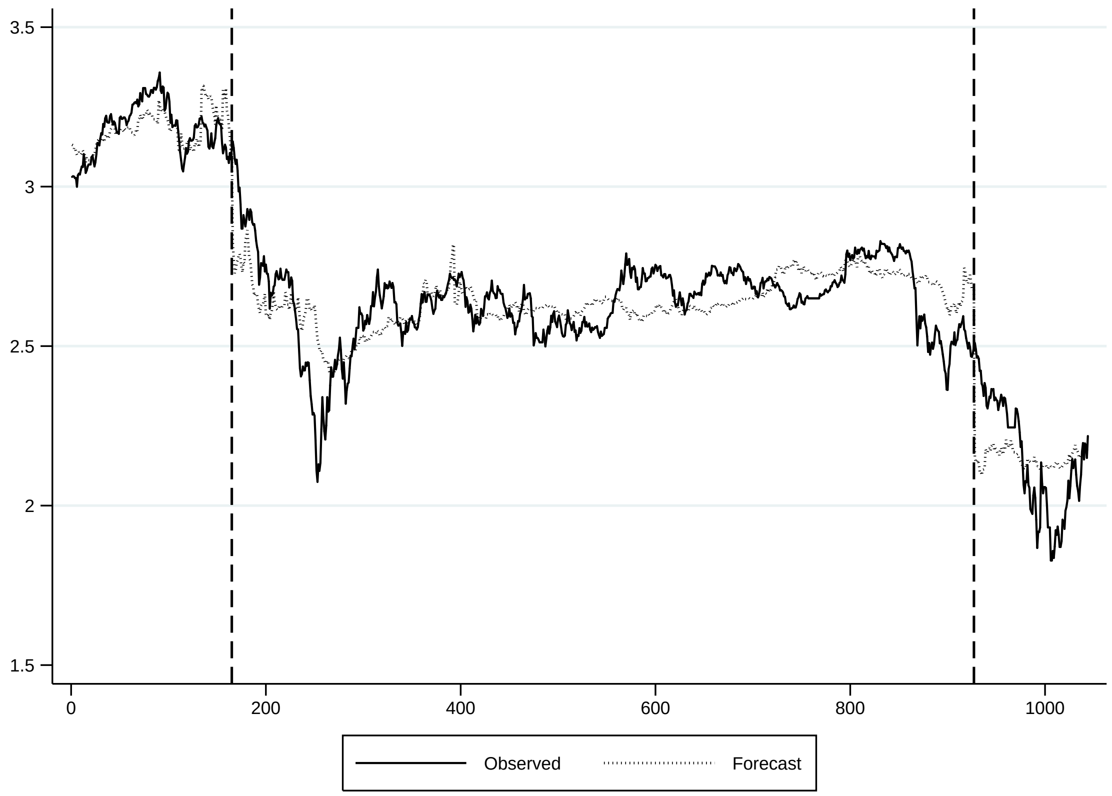


Figure 3: Observed and forecasted carbon price series (in logs).

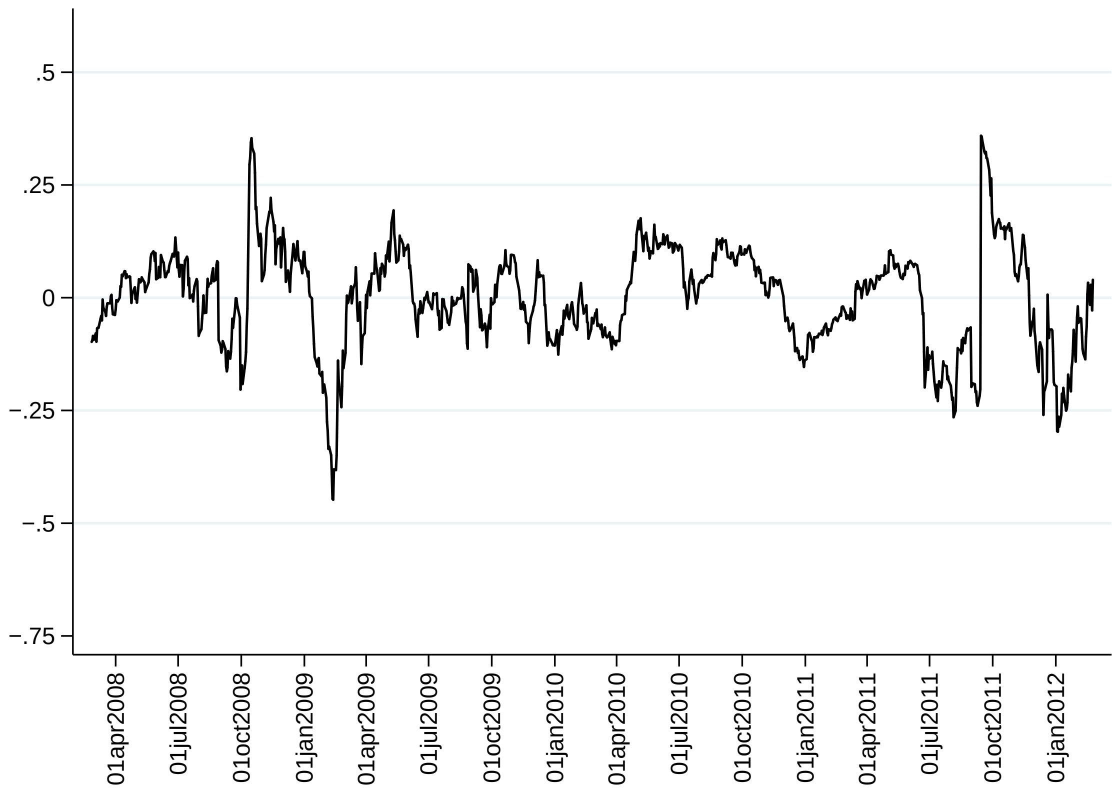


Figure 4: Relative difference between the observed and forecasted carbon price series.

equation (A). I denote by (b) and (c) the short-run equations derived from models (23) and (22), respectively. I denote by (a') the short-run equation as in (a) where discrepancies are those from model (A'). Here also I only focus on the interpretation of the rightmost columns in Table 5. This contains the estimated coefficients of the short-run equations (a) and (a') which correspond to the best specifications of $b_{1t}$.

The estimated coefficient of the speed of adjustment is negative and highly significant. The change in carbon price thus respond to the deviation from the long-run equilibrium (A) in $t-1$. In response to a positive discrepancy in $e_{t-1}$ the carbon price tend to decrease in order to converge toward the long-run equilibrium. This latter result validates my market model, which considers short-run dynamics around a long-run equilibrium. The estimated coefficient on the economic-activity variation refers to the short-run elasticity of the price of carbon relative to the economic activity. This elasticity is positive and highly significant. All else equal, a 1% higher economic activity leads to a rise of 0.332% in the carbon spot price in the short-run. Unlike the long-run equilibrium, both gas and coal prices help determine the carbon-allowance spot price in the short-run. The short-run elasticity of the carbon spot price relative to the gas price is highly significant and almost always positive. The one relative to the coal price is also highly significant and always negative. It varies linearly across the whole gas price range. The higher the gas price is, the higher is the elasticity (in absolute value). These results clearly reveal a trade-off between gas and coal in producing electricity in the short-run.

Table 5: Estimation results of the short-term (error correction) equation

| Model | (c) | (b) | (a) | (a') |
|---|---|---|---|---|
| | Mean equation | | | |
| $\epsilon_{t-1}$ | -0.028*** | -0.022*** | -0.023*** | -0.023*** |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| $\Delta P_t^{gas}$ | 0.072*** | 0.159** | -0.018 | -0.018 |
| | (0.013) | (0.080) | (0.115) | (0.115) |
| $\Delta(P_t^{gas})^2$ | | | 0.121*** | 0.120*** |
| | | | (0.036) | (0.036) |
| $\Delta P_t^{coal}$ | 0.062** | 0.191 | 0.401 | 0.402 |
| | (0.029) | (0.132) | (0.258) | (0.260) |
| $\Delta(P_t^{coal})^2$ | | | 0.127* | 0.125* |
| | | | (0.073) | (0.073) |
| $\Delta(P_t^{gas}P_t^{coal})$ | | -0.038 | -0.288*** | -0.286*** |
| | | (0.037) | (0.102) | (0.101) |
| $\Delta(Eurex_t)$ | 0.329*** | 0.333*** | 0.332*** | 0.332*** |
| | (0.035) | (0.035) | (0.036) | (0.036) |
| $cons$ | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| | Variance equation | | | |
| $ARCH$ | 0.116*** | 0.117*** | 0.117*** | 0.117*** |
| $GARCH$ | 0.874*** | 0.874*** | 0.874*** | 0.874*** |
| $cons$ | 0.000*** | 0.000*** | 0.000*** | 0.000*** |

Note: Standard errors are in (); * ** and *** refer respectively to the 10%, 5% and 1% significance levels of estimated coefficients.

Our results differ from those in Hintermann (2010) who find that only the gas price appear to be related to carbon prices in his base specification. Moreover, in spite of using various extensions of the base specification he does not find any link between the carbon price and economic activity. His results are may be due to the neglected short-run adjustement toward the long-run equilibrium between the price of carbon, fossil fuel prices and economic activity. Indeed, although he claims that there is no cointegration between fuels prices and the emission permit price, creti and al. (2012) found such a cointegration relationship over the first phase of the EU ETS when they account for the structural break of April 2006.

# 4 Conclusion

In this paper I have derived and estimated a structural model of the carbon allowance price during the second phase of the EU ETS. More specifically, relying on the efficient market hypothesis, I estimate a model that specifies an equilibrium relationship between the price of carbon, the gas price and the economic activity on the one hand, and changes in the allowance price as a function of changes in the gas and coal prices, fluctuations in economic activity, and disequilibriums on the other hand. This has revealed differences between the long-term and short-term determinants of the price of carbon allowances. In the long-term, the carbon price depended only on gas prices and the economic activity. The estimated equilibrium relationship shows that the carbon spot price depends on the price of gas in a non-linear way. I find that the carbon spot price experienced two structural changes. The first structural break occured in October 2008 is mainly due to the economic crisis. This was already commented in previous papers. The second break occured in September 2011 is probably the consequence of the economic downturn in late 2011. In the short-run, in addition to the economic activity and the price of gas, the carbon price depended on the coal price. Overall, our results has unveiled that the economic activity strongly impacts the carbon spot price both in the long-term and the short-term. Focusing on fuel prices, the long-term abatement cost and thus the equilibrium price of carbon-allowances depends only on the price of the cleanest energy-source in electricity-generation, while the short-term abatement cost depended on the prices of both clean gas and more polluting coal. This is consistent with an abatement method based on switching from coal toward gas in producing electricity in the short-run. Conversely, the long-term strategies of electricity producers consist perhaps in building gas power plants. However, the crucial hypothesis of efficient markets is questioned when the gas price is below a threshold of 14.35 €$/Mwh$, which occurred from April 2009 to September 2009. Perhaps a market power appears for these low gas prices because of the free allocation of allowances, then dominant participants in the EU ETS behave strategically. As such, the procedure for allocation of allowances in phase III, which schedules the auctioning of more than half of the carbon permits, will be a determining factor in improving the efficiency of the EU

ETS.

# 5 Appendices

## A Derivation of Equation (17) from (16) by recursive solution

I start by restating equation (16):

$$\sum_{k=t+1}^{T}\left(P_k^{CO2}-E_t\left[P_k^{CO2}\right]\right)=\sum_{k=t+1}^{T}\left(b_{1,k}-E_t\left[b_{1,k}\right]\right)+b_2N\widetilde{\beta}\sum_{k=t+1}^{T}\left(\Psi_k-E_{k-1}\left[\Psi_k\right]\right)+\sum_{k=t+1}^{T}e_k$$

If allowances, fuel prices contained in $b_{1k}$ and determinants contained in $\Psi_k$ have the Markov property such that $E_t\left[P_{t+1}\right]=\rho P_t$, where $\rho=1+r$ represent the discount factor and $r$ the interest rate, at time $t=T-1$ (16) can be written as

$$P_T^{CO2}-E_{T-1}\left[P_T^{CO2}\right]=\left(b_{1,T}-E_{T-1}\left[b_{1,T}\right]\right)+b_2N\widetilde{\beta}\left(\Psi_T-E_{T-1}\left[\Psi_T\right]\right)+e_T-E_{T-1}\left[e_T\right]$$

$$P_T^{CO2}-\rho P_{T-1}^{CO2}=\left(b_{1,T}-\rho b_{1,T-1}\right)+b_2N\widetilde{\beta}\left(\Psi_T-\rho\Psi_{T-1}\right)+e_T$$

$$P_T^{CO2}=\rho P_{T-1}^{CO2}+\left(b_{1,T}-\rho b_{1,T-1}\right)+b_2N\widetilde{\beta}\left(\Psi_T-\rho\Psi_{T-1}\right)+e_T \tag{A.1}$$

Now I move one period back to $t=T-2$ then (16) can be written as

$$\begin{aligned}\left[P_{T-1}^{CO2}-E_{T-2}\left[P_{T-1}^{CO2}\right]\right]+\left[P_T^{CO2}-E_{T-2}\left[P_T^{CO2}\right]\right] \;=\; & \left(b_{1,T-1}-E_{T-2}\left[b_{1,T-1}\right]\right)\\ & +\left(b_{1,T}-E_{T-2}\left[b_{1,T}\right]\right)\\ & +b_2N\widetilde{\beta}\left(\Psi_{T-1}-E_{T-2}\left[\Psi_{T-1}\right]\right)\\ & +b_2N\widetilde{\beta}\left(\Psi_T-E_{T-2}\left[\Psi_T\right]\right)\\ & +\left(e_{T-1}-E_{T-2}\left[e_{T-1}\right]\right)\\ & +\left(e_T-E_{T-2}\left[e_T\right]\right)\end{aligned}$$

$$
\begin{aligned}
\left[P_{T-1}^{CO2} - \rho P_{T-2}^{CO2}\right] + \left[P_T^{CO2} - E_{T-2}\left[E_{T-1}\left(P_T^{CO2}\right)\right]\right] \;=\; & (b_{1,T-1} - \rho b_{1,T-2}) \\
& + (b_{1,T} - E_{T-2}\left[E_{T-1}(b_{1,T})\right]) \\
& + b_2 N \widetilde{\beta}\,(\Psi_{T-1} - \rho\Psi_{T-2}) \\
& + b_2 N \widetilde{\beta}\,(\Psi_T - E_{T-2}(E_{T-1}(\Psi_T))) \\
& + e_{T-1} + e_T
\end{aligned}
$$

$$
\begin{aligned}
\left[P_{T-1}^{CO2} - \rho P_{T-2}^{CO2}\right] + \left[P_T^{CO2} - E_{T-2}\left[\rho P_{T-1}^{CO2}\right]\right] \;=\; & (b_{1,T-1} - \rho b_{1,T-2}) \\
& + (b_{1,T} - E_{T-2}(\rho b_{1,T-1})) \\
& + b_2 N \widetilde{\beta}\,(\Psi_{T-1} - \rho\Psi_{T-2}) \\
& + b_2 N \widetilde{\beta}\,(\Psi_T - E_{T-2}\left(\rho\Psi_{T-1}\right)) \\
& + e_{T-1} + e_T
\end{aligned}
$$

$$
\begin{aligned}
\left[P_{T-1}^{CO2} - \rho P_{T-2}^{CO2}\right] + \left[P_T^{CO2} - \rho E_{T-2}\left[P_{T-1}^{CO2}\right]\right] \;=\; & (b_{1,T-1} - \rho b_{1,T-2}) \\
& + (b_{1,T} - \rho E_{T-2}(b_{1,T-1})) \\
& + b_2 N \widetilde{\beta}\,(\Psi_{T-1} - \rho\Psi_{T-2}) \\
& + b_2 N \widetilde{\beta}\,(\Psi_T - \rho E_{T-2}\left(\Psi_{T-1}\right)) \\
& + e_{T-1} + e_T
\end{aligned}
$$

$$
\begin{aligned}
\left[P_{T-1}^{CO2} - \rho P_{T-2}^{CO2}\right] + \left[P_T^{CO2} - \rho^2 P_{T-2}^{CO2}\right] \;=\; & (b_{1,T-1} - \rho b_{1,T-2}) + \left(b_{1,T} - \rho^2 b_{1,T-2}\right) \\
& + b_2 N \widetilde{\beta}\left[(\Psi_{T-1} - \rho\Psi_{T-2}) + (\Psi_T - \rho^2\Psi_{T-2})\right] \\
& + e_{T-1} + e_T
\end{aligned}
$$

$$
\begin{aligned}
P_{T-1}^{CO2} + P_T^{CO2} = (\rho + \rho^2) P_{T-2}^{CO2} + (b_{1,T-1} - \rho b_{1,T-2}) + \left(b_{1,T} - \rho^2 b_{1,T-2}\right) \\
+ b_2 N \widetilde{\beta}\left[(\Psi_{T-1} - \rho\Psi_{T-2}) + (\Psi_T - \rho^2\Psi_{T-2})\right] + e_{T-1} + e_T
\end{aligned}
$$

Substituting (A1) for $P_T^{CO2}$ and rearranging yields

$$\begin{aligned} P_{T-1}^{CO2} + \rho P_{T-1}^{CO2} = (\rho + \rho^2) P_{T-2}^{CO2} + (b_{1,T-1} - \rho b_{1,T-2}) + \left(\rho b_{1,T-1} - \rho^2 b_{1,T-2}\right) \\ + b_2 N \widetilde{\beta} \left[(\Psi_{T-1} - \rho \Psi_{T-2}) + (\rho \Psi_{T-1} - \rho^2 \Psi_{T-2})\right] + e_{T-1} \end{aligned}$$

$$\begin{aligned} (1+\rho) P_{T-1}^{CO2} = (1+\rho)\rho P_{T-2}^{CO2} + (1+\rho) b_{1,T-1} - (1+\rho)\rho b_{1,T-2} \\ + (1+\rho) b_2 N \widetilde{\beta} \left[\Psi_{T-1} - \rho \Psi_{T-2}\right] + e_{T-1} \end{aligned}$$

Dividing both sides of the equation by $(1+\rho)$ yields

$$P_{T-1}^{CO2} = \rho P_{T-2}^{CO2} + (b_{1,T-1} - \rho b_{1,T-2}) + b_2 N \widetilde{\beta} \left[\Psi_{T-1} - \rho \Psi_{T-2}\right] + \frac{e_{T-1}}{1+\rho} \tag{A.2}$$

Moving another period back to $t = T-3$

$$\begin{aligned} P_{T-2}^{CO2} + P_{T-1}^{CO2} + P_T^{CO2} = (\rho + \rho^2 + \rho^3) P_{T-3}^{CO2} + (b_{1,T-2} + b_{1,T-1} + b_{1,T}) \\ - (\rho + \rho^2 + \rho^3) b_{1,T-3} \\ + b_2 N \widetilde{\beta} \left[\Psi_{T-2} + \Psi_{T-1} + \Psi_T - (\rho + \rho^2 + \rho^3) \Psi_{T-3}\right] \\ + e_{T-2} + e_{T-1} + e_T \end{aligned}$$

Substituting (A1) and simplifying gives

$$\begin{aligned} P_{T-2}^{CO2} + (1+\rho) P_{T-1}^{CO2} = (\rho + \rho^2 + \rho^3) P_{T-3}^{CO2} + (b_{1,T-2} + (1+\rho) b_{1,T-1}) \\ - (\rho + \rho^2 + \rho^3) b_{1,T-3} \\ + b_2 N \widetilde{\beta} \left[\Psi_{T-2} + (1+\rho) \Psi_{T-1} - (\rho + \rho^2 + \rho^3) \Psi_{T-3}\right] \\ + e_{T-2} + e_{T-1} \end{aligned}$$

Substituting (A2) and simplifying gives

$$\begin{aligned} \left[1 + \rho + \rho^2\right] P_{T-2}^{CO2} = (\rho + \rho^2 + \rho^3) P_{T-3}^{CO2} + \left[1 + \rho + \rho^2\right] b_{1,T-2} - (\rho + \rho^2 + \rho^3) b_{1,T-3} \\ + b_2 N \widetilde{\beta} \left[\left[1 + \rho + \rho^2\right] \Psi_{T-2} - (\rho + \rho^2 + \rho^3) \Psi_{T-3}\right] + e_{T-2} \end{aligned}$$

$$\left[1+\rho+\rho^2\right] P_{T-2}^{CO2} = \rho\left[1+\rho+\rho^2\right] P_{T-3}^{CO2} + \left[1+\rho+\rho^2\right]\left[b_{1,T-2}-\rho b_{1,T-3}\right] + \left[1+\rho+\rho^2\right] b_2 N\widetilde{\beta}\left[\Psi_{T-2}-\rho\Psi_{T-3}\right] + e_{T-2}$$

Dividing both sides of the equation by $(1+\rho+\rho^2)$ yields

$$P_{T-2}^{CO2} = \rho P_{T-3}^{CO2} + (b_{1,T-2}-\rho b_{1,T-3}) + b_2 N\widetilde{\beta}\left[\Psi_{T-2}-\rho\Psi_{T-3}\right] + e_{T-2} \tag{A.3}$$

The next step would be to move to period $t = T-4$ and successively substituting (A1), (A2) and (A3). However, the general solution is apparent:

$$P_t^{CO2} = \rho P_{t-1}^{CO2} + (b_{1,t}-\rho b_{1,t-1}) + b_2 N\widetilde{\beta}\left[\Psi_t-\rho\Psi_{t-1}\right] + e_t$$

# B The Perron-Vogelsang test

The Perron-Vogelsang (1992) test with a change in the mean using the *AO* procedure implemented on a series $y$ is based on the estimation of the following equation:

$$y_t = \mu + \delta DU_t + \widetilde{y_t}$$

Here $DU_t = 1$ for $t \succ T_b$ and 0 otherwise. $T_b$ is the date of the structural break and will be identified by the scan method. The noise from this equation is the dependent variable in the following equation:

$$\widetilde{y_t} = \sum_{i=1}^{k} \omega_i DT_{b,t-i} + \rho\widetilde{y_{t-1}} + \sum_{i=1}^{k} \theta_i \Delta\widetilde{y_{t-i}} + e_t$$

Here $DT_{b,t} = 1$ for $t = T_b + 1$ and 0 otherwise. This equation is estimated for each date $T_b$ to identify the smallest t-statistic for the unit-root hypothesis, which is then compared with the values tabulated by Perron Vogelsang. In addition, the same test applied to the $y_t$ series using the *IO* procedure is based on the estimation of the following equation:

$$y_t = \mu + \delta DU_t + \varphi DT_{b,t} + \rho y_{t-1} + \sum_{i=1}^{k} \theta_i \Delta y_{t-i} + e_t$$

Testing the unit root hypothesis is equivalent to testing whether the coefficient $\rho$ is significantly less than 1.

## C The Clemente Montanès and Reyes test

The Clemente Montanès and Reyes (1998) test with a double change in the mean (1998) using the $AO$ procedure implemented on a series $y$ is based on the estimation of the following equation:

$$y_t = \mu + \delta_1 DU_{1t} + \delta_2 DU_{2t} + \widetilde{y_t}$$

Here $DU_{mt} = 1$ for $t \succ T_{bm}$ and 0 otherwise, for $m = 1, 2$. $T_{b1}$ *et* $T_{b2}$ are the dates of the structural breaks and will be identified by the scan method. The noise from this equation is the dependent variable in the following equation:

$$\widetilde{y_t} = \sum_{i=1}^{k} \omega_{1i} DT_{b1,t-i} + \sum_{i=1}^{k} \omega_{2i} DT_{b2,t-i} + \rho \widetilde{y_{t-1}} + \sum_{i=1}^{k} \theta_i \Delta \widetilde{y_{t-i}} + e_t$$

Here $DT_{bm,t} = 1$ for $t = T_{bm} + 1$ and 0 otherwise for $m = 1, 2$. This equation is estimated for each pair $(T_{b1}, T_{b2})$ to identify the smallest t-statistic for the unit-root hypothesis, which is then compared with the values tabulated by Clemente Montanès and Reyes. In addition, the same test applied to the $y_t$ series using the $IO$ procedure is based on the estimation of the following equation:

$$y_t = \mu + \delta_1 DU_{1t} + \delta_2 DU_{2t} + \varphi_1 DT_{b1,t} + \varphi_2 DT_{b2,t} + \rho y_{t-1} + \sum_{i=1}^{k} \theta_i \Delta y_{t-i} + e_t$$

Testing the unit root hypothesis is equivalent to testing whether the coefficient $\rho$ is significantly less than 1.

## D Carbon spot price stationarity tests in the presence of breaks

Table 6: Results of stationnarity tests in the presence of breaks applied to carbon spot price (in logs)

| Test | Clementes Montan ès and Reyes test | | | | Perron Vogelsang test | | | |
|---|---|---|---|---|---|---|---|---|
| Procedure | IO | | AO | | IO | | AO | |
| Series | Level | Variation | Level | Variation | Level | Variation | Level | Variation |
| $DU_1$ | -0.0182*** | 0.003* | -0.531*** | 0.004** | -0.006** | -0.002 | -0.576*** | -0.003* |
| | (-4.54) | (1.86) | (-48.52) | (2.30) | (-2.23) | (1.52) | (-36.82) | (1.95) |
| $DU_2$ | -0.016*** | -0.002 | -0.593*** | -0.003 | | | | |
| | (-4.27) | (-1.15) | (-33.42) | (-1.59) | | | | |
| $\rho$-1 | -0.031 | -0.968 | -0.031 | -0.976 | -0.008 | -0.955 | -0.010 | -1.059 |
| | (-5.06) | (-18.31) | (-3.43) | (-7.29) | (-2.426) | (-18.03) | (-2.00) | (-10.38) |
| | [-5.49] | [-5.49] | [-5.49] | [-5.49] | [-4.19] | [-4.19] | [-3.61] | [-3.61] |
| Conclusion | I(1) | I(0) | I(1) | I(0) | I(1) | I(0) | I(1) | I(0) |
| Dates of | 13/10/08 | | 21/11/08 | 17/02/09 | 29/08/11 | | 21/11/08 | |
| Breaks | 14/09/11 | | 28/11/11 | | | | | |

Note: The values in () and [] are respectively the t-statistics and the critical values at significance level of 5% tabulated by Clemente Montanès and Reyes on the one hand and by Perron and Vogelsang on the other. The null hypothesis of unit root is rejected when the t-statistique is smaller than the critical value. * ** and *** refer respectively to the 10%, 5% and 1% significance levels of estimated coefficients of the dummies variables.

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