

Chapter 2

CO₂ Price Fundamentals

Abstract This chapter details the main carbon price drivers related to (i) institutional decisions, (ii) energy prices and (iii) weather events. First, we review the econometric techniques based on dummy variables and structural breaks which may be useful to detect how institutional news announcements affect the price path of carbon. Second, we detail how energy prices related to fuel use (brent, natural gas, coal) and power producers' fuel-switching behavior (clean dark spread, clean spark spread, switch price) impact carbon price changes through various regression models. Third, we detail the economic rationale behind the influence of extreme weather events on carbon prices, based on unanticipated temperatures changes. The Appendix presents an extension of the econometric framework on the basis of multivariate GARCH modelling between energy and CO₂ prices.

2.1 Institutional Decisions

The price path of CO₂ allowances under the EU ETS is deeply affected by institutional decisions. Indeed, the EU ETS is an environmental market, which has been created by the Directive 2003/87/EC. According to this environmental regulation tool, the EU Commission and more particularly the Directorate-General for Climate Action (DG CLIMA) can intervene to amend the functioning of the scheme. As market participants fully react to news arrival, any policy intervention from the regulator has an immediate impact on the carbon price (Mansanet-Bataller and Pardo ([41], 2009), Daskalakis and Markellos ([20], 2009), Conrad et al. ([17], 2011)).

2.1.1 Dummy Variables

The influence of institutional decisions is classically captured in time-series econometrics by using dummy variables. We explain the main logic behind using this econometric tool, along with a hands-on example.

2.1.1.1 Basic Principle

Dummy variables are useful to capture the presence or the absence of a given phenomenon. They can be introduced in the multiple regression model when one wants

to take into account, among other explanatory variables, the effect of a binary explanatory factor. These binary variables are composed of zeros throughout the period (chronologically ordered in days) in the absence of the phenomenon under consideration. When one institutional event is expected to affect the carbon price, it is coded as one in the dummy variable. For instance, a news announcement by the EU Commission concerning changes in the allocation methodology for the EU ETS is supposed to be immediately integrated by market agents and it will be reflected in the current carbon price. On that specific day, we will set the dummy variable to be equal to one.

Next, by regressing carbon price changes on the dummy variable, we evaluate the significant impact of such institutional events on the price path of carbon at usual statistical levels. As mentioned earlier, the main interest behind dummy variables lies in their ability to be added to other more traditional explanatory variables. It is noteworthy to remark that the introduction of dummy variables modifies neither the estimation methods, nor the statistical tests, of the multiple regression model.

2.1.1.2 A Practical Example

The following example can be replicated by the interested reader by using the R software.¹ The dataset used in this example can be downloaded at: http://sites.google.com/site/jpchevallier/publications/books/springer/data_chapter2.csv.

To illustrate how to use dummy variables, we wish to evaluate the impact of news about Phase II and Phase III National Allocation Plans (NAPs) by the European Commission on the price of carbon. To do so, we have identified the news announcements summarized in Table 2.1. The dummy variables refer to news information disclosure concerning NAPs Phase II (*NAPsPhaseII*), and Phase III (*NAPsPhaseIII*). The main sources for the news events recorded may be cited as being: the UNFCCC, the European Commission, the European Parliament, the European Economic and Social Committee, ECX, EEX, Bluenext, ICE, and Point Carbon.

The period under consideration goes from March 9, 2007 to March 31, 2009, i.e. it covers a sample of 529 daily observations. During the days when no news event falling in either of the two categories was recorded, the dummy variables take the value of zero as explained in Sect. 2.1.1.1.

Box 2.1 (Stationarity and Unit Root Tests) Before estimating any time series model, it is necessary to test for the stationarity of the dependent variable (and independent variables as well in ARMAX models). Dickey-Fuller (1979, [24]) test the nullity of the coefficient α in the following regression:

$$\Delta x_t = x_{t+1} - x_t = \alpha x_t + \beta + e_t \quad (2.1)$$

¹R is a free software environment for statistical computing and graphics. It can be downloaded at: <http://www.r-project.org/>. See [46] for an introduction.

Table 2.1 Dummy Variables

	Date	NAPs Phase II	NAPs Phase III
	26/03/2007	1	0
	26/03/2007	1	0
	02/04/2007	1	0
	04/05/2007	1	0
	15/05/2007	1	0
	04/06/2007	1	0
	13/07/2007	1	0
	18/07/2007	1	0
	31/08/2007	1	0
	22/10/2007	1	0
	26/10/2007	1	0
	26/10/2007	1	0
	26/10/2007	1	0
	07/12/2007	1	0
	23/01/2008	0	1
	28/02/2008	0	1
	03/03/2008	0	1
	05/06/2008	0	1
	06/06/2008	0	1
	11/06/2008	0	1
	09/07/2008	0	1
	07/10/2008	0	1
	08/10/2008	0	1
	15/10/2008	0	1
Source: UNFCCC, European	20/10/2008	0	1
Commission, European	04/12/2008	0	1
Parliament, European	17/12/2008	0	1
Economic and Social	17/12/2008	0	1
Committee, ECX, EEX,	17/12/2008	0	1
Bluenext, ICE, Point Carbon	17/12/2008	0	1

- if α is significantly negative, then we say that the process x_t has no unit root, or that it is stationary, inducing a mean-reverting behavior for the prices;
- if α is not significantly different from 0, then we say that the process x_t ‘has a unit root’, inducing a random walk behavior for the prices.

In practice, the Augmented-Dickey-Fuller (1981, ADF, [25]) or Phillips-Peron (1988, PP, [44]) tests are used rather than Dickey-Fuller. These tests are based on the same principle but correct for potential serial autocorrelation and time trend in Δx_t through a more complicated regression:

$$\Delta x_t = \sum_{i=1}^L \beta_i \Delta x_{t-i} + \alpha x_t + \beta_1 t + \beta_2 + e_t \quad (2.2)$$

The ADF test tests the null hypothesis H_0 that $\alpha = 0$ (the alternative hypothesis H_1 being that $\alpha < 0$) by computing the Ordinary Least Squares (OLS) estimate of α in the previous equation and its t -statistics $\hat{t}$; then, the statistics of the test is the t -statistics $\hat{t}_\alpha$ of coefficient α , which follows under H_0 a known law (studied by Fuller and here denoted Ful). The test computes the p -value p , which is the probability of $Ful \leq \hat{t}$ under H_0 . If $p < 0.05$, H_0 can be safely rejected and H_1 accepted: we conclude that the series ' x_t has no unit root'. Extensions of these stationarity tests were also developed by Kwiatkowski, Phillips, Schmidt, and Shin (1992, KPSS, [39]). This task can easily be performed in R, as shown below:

```
1 library(tseries)
2 adf.test(eua)
3 PP.test(eua)
4 kpss.test(eua)
```

Line 1 loads the relevant library. Line 2 performs the ADF test on the properly transformed EUA time series. Lines 3 and 4 compute, respectively, the PP and KPSS tests. The user can also choose between various lags (command `lags`) and deterministic (command `type="trend"`) or stochastic (command `type="drift"`) specifications for the tests (see [8] for a review).

To capture the influence of these institutional news events on the price of carbon, we run the following regression:

$$y_t = \alpha + \phi y_{t-1} + \beta NAPsPhaseII_t + \theta NAPsPhaseIII_t + \varepsilon_t \quad (2.3)$$

with y_t the dependent carbon price variable (taken in log first-difference), α the constant term, ϕ the parameter capturing the influence of the AR(1) process, β the parameter capturing the influence of the dummy variable $NAPsPhaseII$, θ the parameter capturing the influence of the dummy variable $NAPsPhaseIII$, and ε_t the error term.

Box 2.2 (ARIMA(p, d, q) Modeling of Time Series) According to Wold's theorem, a non-stationary and stochastic time series can be modeled as an AutoRegressive Integrated Moving Average (ARIMA) process:

$$\Phi(L)(1-L)^d X_t = \Theta(L)\varepsilon_t \quad (2.4)$$

with L the lag operator, p the AR order, q the MA order, and d the integration order. The time series needs to be transformed d times to exhibit stationarity properties (see Hamilton (1996, [33] for a detailed coverage).

Table 2.2 R Code: Linear regression with dummy variables

```

1  path<-"C:/"
2  setwd(path)
3  library(dynlm)
4  data=read.csv("data_chapter2.csv",sep=",")
5  attach(data)
6  eua=data[,2]
7  napII=data[,3]
8  napIII=data[,4]
9  model<-dynlm(eua~L(eua)+napII+napIII)
10 summary(model)
11 layout(matrix(1:4,2,2))
12 plot(model)
13 acf(residuals(model))
14 acf(residuals(model),type='partial')

```

The ARIMA modeling of a given time series can be achieved in R with the commands:

```

1 library(stats)
2 model<-arima(eua,order=c(1,0,0))

```

Line 2 features the AR(1) part of the data generating process, which can contain three components (p, d, q). p is the AR order. d is the degree of differencing. q is the MA order (see [33]). Note that external regressors can optionally be added with the argument `xreg`.

To estimate the dynamic linear model in Eq. (2.3) with time series regression relationships, the interested reader may run the computer code contained in Table 2.2 under the R software.

Lines 1–2 specify the user’s working directory. Line 3 loads the R library ‘dynlm’, which needs to be pre-installed by the user. Lines 4 to 8 load the data. Line 9 estimates the dynamic linear model in Eq. (2.3). Line 10 produces the regression results shown in Table 2.3.

We can see that the coefficient estimate for the AR(1) process is highly significant (at the 1% level). Other coefficient estimates for the dummy variables *NAPsPhaseII* and *NAPsPhaseIII* are not statistically significant. In this illustrative example, we fail to detect the effects of news announcements about allocation methodologies on the price of carbon.

Looking at the residuals estimated, the output gives us a superficial view of the distribution of the residuals, which may be used as a quick check of the distributional assumptions [22]. Note that the average of the residuals is zero by definition, so the median should not be far from zero, and the minimum and maximum should roughly be equal in absolute value. In our setting, the first and third quartiles are remarkably close to zero.

Table 2.3 R Output: Linear regression with dummy variables

Call:
dynlm(formula = eua ~ L(eua) + napII + napIII)

Residuals:

Min	1Q	Median	3Q	Max
-1.289e-17	-5.985e-19	-1.492e-19	4.469e-19	2.938e-17

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.000e+00	9.940e-20	0.000e+00	1.000
L(eua)	1.000e+00	2.684e-18	3.725e+17	<2e-16 ***
napII	-4.338e-19	6.519e-19	-6.650e-01	0.506
napIII	5.498e-19	6.271e-19	8.770e-01	0.381

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.231e-18 on 525 degrees of freedom

Multiple R-squared: 1, Adjusted R-squared: 1

F-statistic: 4.637e+34 on 3 and 525 DF, p-value: < 2.2e-16

Next, the residual standard error is the residual variation, i.e. an expression of the variation of the observations around the regression line, estimating the variance of the model parameters. Besides the R-squared and Adjusted R-squared statistics, the F-statistics is an F test for the hypothesis that the regression coefficient is zero. These latter diagnostic tests are not really interesting in this practical example. They will be more useful later in this chapter as we introduce more explanatory variables.

Finally, lines 11 to 14 show several residual plots. Let us describe the different panels in Fig. 2.1. The upper left panel provides a graph of residuals versus fitted values, perhaps the most familiar of all diagnostic plots for residual analysis [38]. It is useful for checking the assumption that $E(\varepsilon|X) = 0$, as the regressions and confidence intervals used in Eq. (2.3) are based on the assumption of i.i.d. normal errors. In our setting, we can observe some clustering and irregular variations in the residuals, which suggests that the model is mis-specified. The bottom left panel is a Quantile-Quantile plot for normality, whose curvature (or rather its lack thereof) shows whether the residuals are more or less conform with normality. The insight behind a QQ-plot is that the residuals can be assessed for normality by comparing them to “ideal” normal observations. The upper and bottom right panels are a scale-location plot and a plot of standardized residuals against leverages, respectively. They are useful for checking the assumption that errors are identically distributed, and to display combinations of standardized residuals, leverage, and Cook’s distance.²

²For further details on how to interpret regression diagnostics for linear models, see [38].

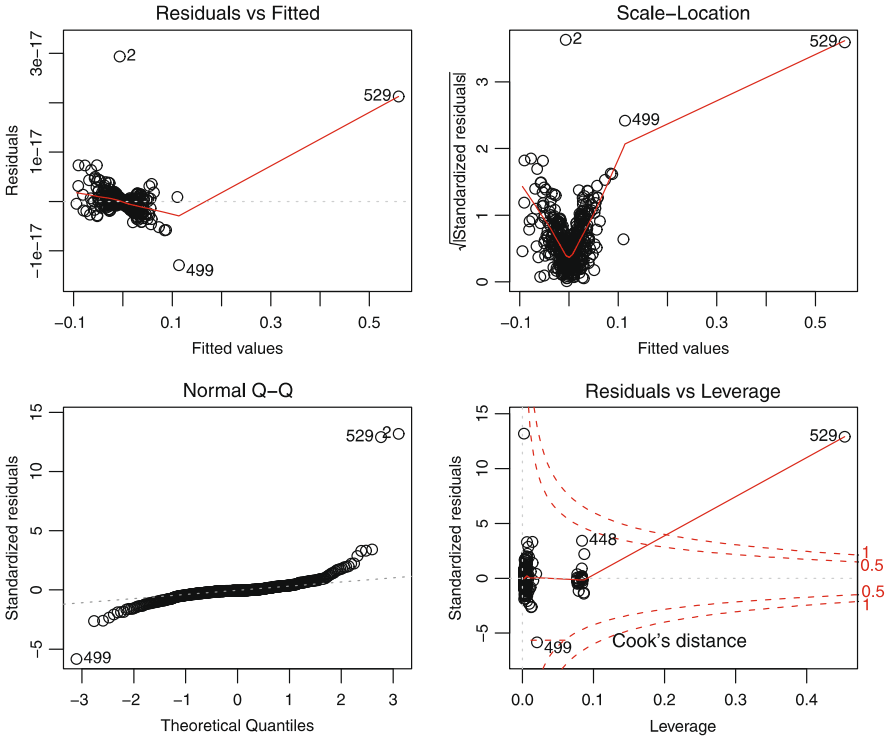


Fig. 2.1 Diagnostic plots for the model estimated in Eq. (2.3)

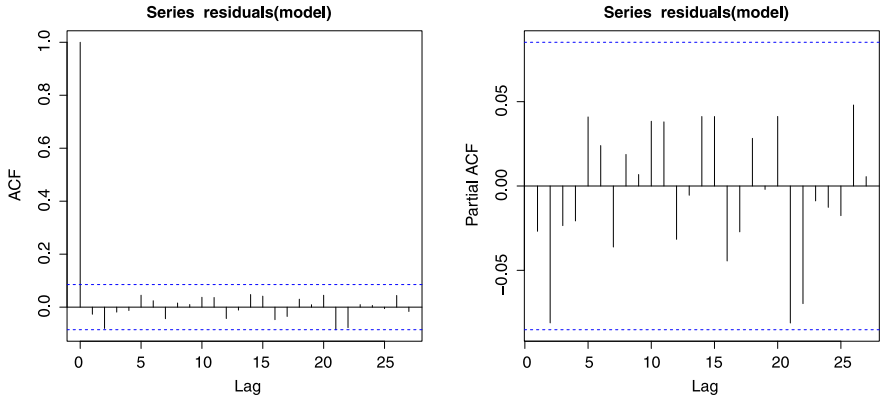


Fig. 2.2 Autocorrelation and partial-autocorrelation functions for the residuals from the model estimated in Eq. (2.3)

Figure 2.2 shows the autocorrelation (ACF) and partial-autocorrelation (PACF) functions of the residuals. The broken horizontal lines on the plots correspond to

95-percent confidence limits. The general pattern of the autocorrelation and partial autocorrelation functions—one positive spike in the former; sinusoidal decay in the latter—is indicative of an AR(1) process.

Box 2.3 (The Ljung-Box-Pierce Residual Autocorrelation Test) Under the null hypothesis of no autocorrelation in the residuals, noted $\hat{\varepsilon}_t = \frac{\hat{\phi}(L)}{\hat{\theta}(L)} X_t$:

$$\hat{\rho}_{1(\hat{\varepsilon}_t)} = \hat{\rho}_{2(\hat{\varepsilon}_t)} = \cdots = \hat{\rho}_{K(\hat{\varepsilon}_t)} = 0 \quad (2.5)$$

the Box-Pierce ‘portmanteau’ test statistic writes:

$$BP(K) = T \sum_{k=1}^K \hat{\rho}_{k(\hat{\varepsilon}_t)}^2 \quad (2.6)$$

with T the number of observations, $\hat{\rho}_{k(\hat{\varepsilon}_t)}$ the autocorrelation coefficient of order k of the estimated residuals, and K the maximum number of lags. Under the assumption that X_t is an i.i.d. sequence with certain moment conditions, $BP(K)$ is asymptotically a χ^2 random variable with $(K - p - q)$ degrees of freedom (see Hamilton (1996, [33]) for further details).

Ljung-Box have modified this statistic to increase the power of the test in finite samples:

$$LB(K) = T(T + 2) \sum_{k=1}^K \frac{\hat{\rho}_{k(\hat{\varepsilon}_t)}^2}{T - k} \quad (2.7)$$

Similarly, $LB(K)$ is asymptotically a χ^2 random variable with $(K - p - q)$ degrees of freedom.

To test formally for the presence of autocorrelation in the residuals, the Ljung-Box-Pierce test can be performed in R:

```
1 library(tseries)
2 Box.test(eua)
```

This code computes the Box-Pierce or Ljung-Box test statistic for examining the null hypothesis of independence in a given time series (see [34]).

Next, we explore another methodology to detect the effects of institutional decisions on the price path of carbon, based on structural break tests.

2.1.2 Structural Breaks

In what follows, we explain first the rationale behind relating institutional decisions to structural breaks. Second, we provide an empirical application to the EUA time series.

Table 2.4 R Code: Bai-Perron Structural Break Test

```

1  path<-"C:/"
2  setwd(path)
3  library(strucchange)
4  data=read.csv("data_chapter2.csv",sep=",")
5  attach(data)
6  eua=data[,2]
7  bp.ri <- breakpoints(eua ~ 1, h = 30)
8  summary(bp.ri)
9  plot(bp.ri)
10 coef(bp.ri, breaks = 3)
11 vcov(bp.ri, breaks = 3, vcov = kernHAC)
12 confint(bp.ri, breaks = 3, vcov = kernHAC)

```

2.1.2.1 Structure of the Test

The influence of institutional decisions on the price path of carbon may also be detected by means of structural break tests. Formally, the concept of structural break may be defined as changes in the underlying structural relationship within an economy. More intuitively, it can be said that structural breaks occur in a time series when the structure of the data generating mechanism underlying a set of observations changes. Therefore, our econometric approach consists here in detecting when shocks occur in the carbon price series, and to attempt to relate such shocks to institutional news announcements by the EU Commission.

Bai and Perron have developed very popular techniques to estimate and test linear models with multiple structural changes [5–7]. By borrowing notations from [47], we briefly recall below the multiple linear regression model with m breaks (or, equivalently, $m + 1$ regimes):

$$y_t = x_t^\top \delta_j + u_t, \quad t = T_{j-1} + 1, \dots, T_j, \quad j = 1, \dots, m + 1 \quad (2.8)$$

with T the sample size, $T_0 = 0$ and $T_{m+1} = T$. The goal of the analysis is to determine the number and location of the breakpoints T_j , $j = 1, \dots, m$. A search over m is conducted, for $m \leq m^*$, where m^* is fixed by the researcher. The minimum number of observations per segment, h , can also be exogenously set by the user.³

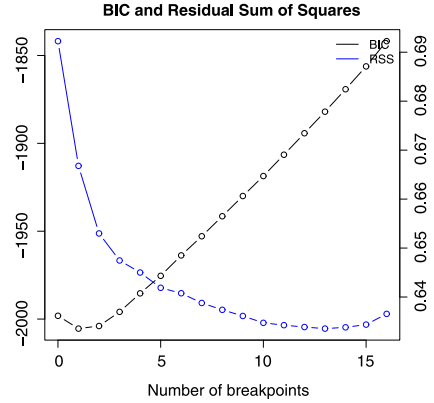
2.1.2.2 Empirical Application

Let us apply this analysis to carbon price data by using the R code contained in Table 2.4.

As previously, lines 1 to 6 load the relevant libraries (pre-installed by the user) and data. Line 7 specifies a linear model in which the dependent variable *EUA* is

³Note this may be considered as a bandwidth or trimming parameter.

Fig. 2.3 EUA: RSS and BIC for models with up to sixteen breaks



modeled by just an intercept. Line 8 produces the estimation output (not reproduced here because of its length), which comprises a triangular matrix containing the residual sums of squares (RSS), the extraction of breakpoints, corresponding information criteria, coefficient estimates and confidence intervals as described by Bai and Perron [5–7]. Line 9 plots all models with $m = 1, \dots, 16$ breaks along with the corresponding values of the Bayesian Information Criterion (BIC) and the RSS.

As shown in Fig. 2.3, the BIC selects two breaks $m = 2$. However, because information criteria are often downward-biased, Bai and Perron argue in favor of the presence of an additional break. That is why we proceed with the estimation of a three-break model in lines 10–11. The output (not shown here) returns coefficient estimates with standard errors utilizing a kernel heteroskedasticity and autocorrelation consistent (HAC) estimator.⁴ Line 12 computes the confidence intervals for the three breakpoints.⁵

In Fig. 2.4, we have reproduced the time series of EUA along with the breakpoints and corresponding confidence intervals (at the default 95% level) coded by the observation numbers and by the dates on the underlying time scale. The estimated breakpoints are:

1. May 28, 2007
2. December 30, 2008
3. February 11, 2009

There are considerable differences in the confidence intervals corresponding to the break dates. In this example, it emerges that the intervals for the second and

⁴With a quadratic spectral kernel, prewhitening using a VAR(1) model and an AR(1) approximation for the automatic bandwidth selection (see [47]).

⁵The confidence intervals are derived from the distribution of the argmax functional of a process composed of two independent Brownian motions with different linear drifts and scales (see [5] for further details on this nonstandard distribution). This cumulative distribution function depends on three parameters which are associated with ratios of quadratic forms in the magnitude of the shifts and weighting matrices defined as segment-wise covariance matrices [47].

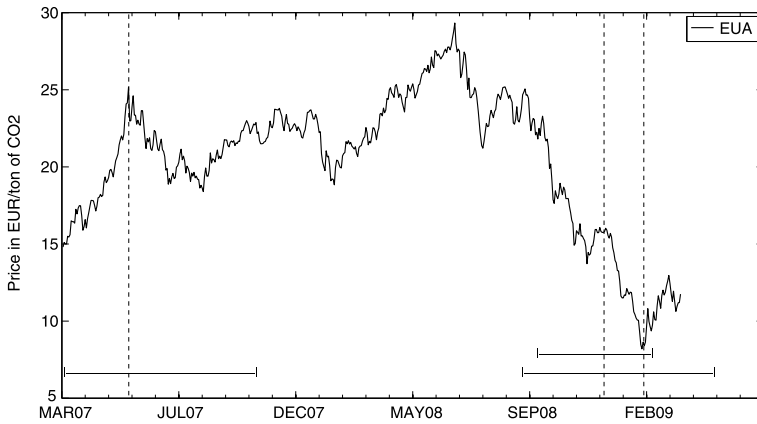


Fig. 2.4 EUA with three breaks (vertical lines) and 95% confidence intervals (horizontal lines)

third breaks overlap. Hence, there appears to be considerable uncertainty as to the location of the second break. Given that information criteria such as the BIC select a model with two breaks and that the decrease of the RSS when passing from a two break to a three break model is small (see Fig. 2.3), these results may be summarized as pointing to two competing models: $m = 2$ or $m = 3$.

Visual inspection hints at the presence of a strong adjustment period during December 2008–February 2009, which corresponds to the impact of the financial crisis on the carbon market [14]. In that case, it may be more appropriate to run separate regressions in sub-samples (before and after the crisis) in order to identify carbon price drivers. Therefore, structural break tests may also be used to delimit full- and sub-samples estimates (see [2] for another application).

The first break is somewhat of smaller magnitude than the other two, and may be related to the 2006 yearly compliance event [15]. Therefore, the first breakpoint may be directly related to the effects of institutional news by the European Commission concerning the publication of yearly verified emissions.

Overall, we have seen how to detect structural breaks in the time series of EUAs, which may then be related to institutional news announcements. In the next section, we extend our analysis to another kind of carbon price drivers: energy prices.

2.2 Energy Prices

The task faced by the econometrician when investigating the empirical properties of carbon prices consists in finding the appropriate market fundamentals. On the supply side, the amount of CO₂ allowances distributed each year according to NAPs are known in advance by all market participants. Hence, there is no uncertainty concerning the number of allowances flowing on the market. On the demand side, carbon prices are impacted by energy prices because it relates to the producing process of the utilities regulated by the EU ETS. As companies pollute (i.e. they emit tons of

CO₂ in the atmosphere), they face essentially two choices: either compensate for the associated pollution (by surrendering allowances from their own registry), or purchase/sell allowances on the market depending on the excess/lack of pollution compared to their annual endowment (and thereby engaging in permits trading). The amount of permits that a given company needs in order to balance its actual CO₂ emissions depends on the type of fuel burned. Coal for instance is far more CO₂ intensive than natural gas. Companies need also to pay attention to the relative variation of energy prices: in case of a rise in the price of oil for instance, the price of many manufactured products (using oil as an input to production or to produce energy) will similarly increase. That is why the price of carbon, and the demand for CO₂ allowances, are linked to the variation of energy prices. Finally, we need to keep in mind that power producers are key players on the carbon market, as they received globally around 50% of allocation each year. Therefore, their fuel-switching behavior (producing one unit of electricity based on coal-fired or gas-fired powerplants, and switching between inputs as their relative price vary) will be a central factor to explain the variation of the carbon price in this chapter.

In what follows, we briefly review the existing literature. Then, we consider several regression models by including oil, natural gas, coal and electricity variables, and explain how they affect the carbon price throughout our econometric analysis.

2.2.1 Literature Review

Following the pioneering work by Christiansen et al. ([16], 2005) and Kanen ([36], 2006), Ellerman and Buchner [26, 27], and Convery and Redmond ([19], 2007) produced the first literature reviews on the carbon price development in their respective articles. This work was further elaborated by Convery ([18], 2009) and Ellerman, Convery and De Perthuis ([28], 2010).

Based on economic analysis (essentially demand and supply fundamentals), Christiansen et al. ([16], 2005) have identified the following factors as being the price determinants in the EU ETS: policy and regulatory issues; market fundamentals, including the emissions-to-cap ratio, the role of fuel-switching, weather and production levels. Mansanet-Bataller et al. ([42], 2007) and Alberola et al. ([2], 2008) were the first analyses to uncover econometrically the relations between energy markets and the CO₂ price. Based on Phase I spot and futures data, the former group of authors establishes that carbon prices in the EU ETS are linked to fossil fuel (e.g., oil, gas, coal) use. By using an extended dataset, the latter group of authors emphasizes that the nature of this relationship between energy and carbon prices varies depending on the period under consideration, and the major influence of institutional events. In addition, Keppler and Mansanet-Bataller ([37], 2010) have studied the causalities between CO₂ and electricity variables (such as clean dark and clean spark spreads, and the switch price) during the first phases of the EU ETS.

Concerning the econometric modelling of the EUA time series, Benz and Trück ([9], 2009) have detailed the modeling of the price dynamics for CO₂ emission

allowances based on GARCH models. Besides Paoletta and Taschini ([43], 2008) have shown how to model the properties of CO₂ spot returns during this very specific period of the end of Phase I. On this topic, it is also worth highlighting the important theoretical contribution by Daskalakis et al. ([21], 2009) under the form of an explicit modeling of the effects of banning banking on pricing CO₂ futures prices during the first phase, and the empirical investigation of these effects by Alberola and Chevallier ([1], 2009).

Bunn and Fezzi ([12], 2009) further quantify the mutual interactions of electricity, gas and carbon prices in the UK. By using a structural, co-integrated vector error-correction model, they derive the dynamic pass-through of carbon prices into electricity prices, and the response of electricity and carbon prices to shocks in the gas price.

Finally, it is worth highlighting the work by Hintermann ([35], 2010), who derives a structural model of the allowance price under the assumption of efficient markets and examines the extent to which this variation in price can be explained by marginal abatement costs. Last but not least, macroeconomic fundamentals of carbon prices have been studied by Alberola et al. ([3], 2008, [4], 2009), as it will be more detailed in Chap. 3.

2.2.2 Oil, Natural Gas and Coal

This section investigates the impact of fuel use (brent, natural gas, coal) on carbon prices. We aim at understanding how carbon prices are impacted by the relative variation of fuel prices as an input to energy production.

2.2.2.1 Recent Evolution

The brent price (expressed in Euro/BBL) is the brent crude futures Month Ahead price negotiated on ICE (Fig. 2.5). The brent is a North Sea deposit: its oil is representative of the crudes produced in this region. Therefore, it provides the best characteristics to match other energy variables traded in continental Europe, which enter in the determination of the carbon price.

The natural gas price used (expressed in Euro/Therm) is the futures Month Ahead natural gas price negotiated on Zeebrugge Hub (Fig. 2.6). It is the most liquid gas trading market in Europe, and has a major influence on the price that European consumers pay for their gas. As such, the Zeebrugge price represents the best proxy of the European gas market price determined close to end-users.

The coal price is the Antwerp/Rotterdam/Amsterdam (ARA) coal futures Month Ahead price (see Fig. 2.7), which is the major imported coal in northwest Europe. The ARA coal is expressed in Euro/ton.

Before proceeding with our regression analysis, it is important to check the matrix of cross-correlations between the carbon price and energy variables (transformed to logreturns). Table 2.5 reveals that no cross-correlation is above 0.6 in absolute value. This step is important in order to detect multi-collinearities that could potentially bias the result estimates from the regression. If multi-collinearities are

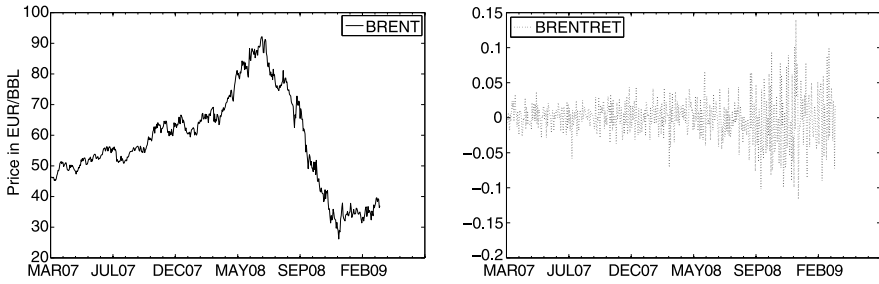


Fig. 2.5 Brent: Raw data (*left panel*) and logreturns (*right panel*) from March 09, 2007 to March 31, 2009

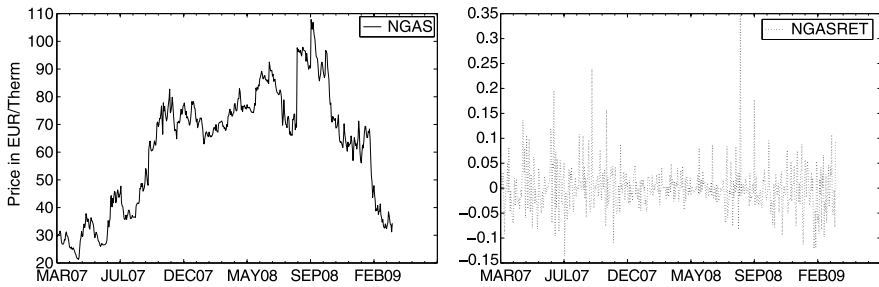


Fig. 2.6 Natural Gas: Raw data (*left panel*) and logreturns (*right panel*) from March 09, 2007 to March 31, 2009

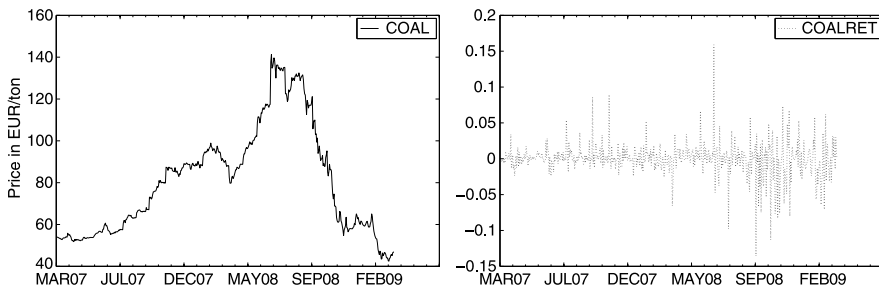


Fig. 2.7 Coal: Raw data (*left panel*) and logreturns (*right panel*) from March 09, 2007 to March 31, 2009

Table 2.5 Cross-correlations between carbon (EUA) and energy (BRENT, NGAS, COAL) variables in logreturns transformation

	EUARET	BRENTRET	NGASRET	COALRET
EUARET	1			
BRENTRET	0.2207	1		
NGASRET	0.1959	0.0978	1	
COALRET	-0.1215	-0.0792	0.0321	1

suspected, the econometrician needs to resort to more formal tests, such as the variance inflation ratio (see [32] for an extensive coverage of this topic).

Box 2.4 (Granger Causality Test) In conjunction with the analysis of the matrix of cross-correlations, the econometrician may resort to Granger causality tests as well. These tests allow to infer causality ‘in the Granger sense’ between a set of dependent and independent variables selected by the user, and may be useful in econometric modelling prior to the regression analysis.

The main insight behind Granger causality testing for two variables X and Y is to evaluate whether the past values of X are useful for predicting Y once Y ’s history has been modeled. The null hypothesis is that the past p values of X do not help in predicting the value of Y .

The test is implemented by regressing Y on p past values of Y and p past values of X . An F -test is then used to determine whether the coefficients of the past values of X are jointly zero. Under the null hypothesis that X does not cause Y , the non-constrained model (NC) writes $Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 X_{t-1} + \varepsilon_t$. The constrained model (C) writes $Y_t = \alpha + \beta_1 Y_{t-1} + \varepsilon_t$. The Fisher test-statistic is computed as $F^* = \frac{(SSR_C - SSR_{NC})/c}{SSR_{NC}/(n-k-1)}$ with SSR the sum of squared residuals, c the number of restrictions (i.e. the number of coefficients whose nullity are tested), and k the number of variables. If F^* is superior to the critical value found in the Fisher statistical law with $(1, n - 2)$ degrees of freedom, then the null hypothesis (causality from X to Y) is rejected.

The code below illustrates how to perform Granger causality testing in R:

```
1 library(MSBVAR)
2 granger.test(eua, p=2)
```

where p is the past value (or lag) set by the user. The results from linear Granger causality tests are known to be sensitive to the choice of the lag. Therefore, the user may experiment with various lags in order to test the robustness of the conclusions obtained.

2.2.2.2 Regression Analysis

To illustrate our analysis on the expected impacts of energy variables on the carbon price, we run the following regression:

$$y_t = \alpha + \beta_1 \text{Brent}_t + \beta_2 \text{NGas}_t + \beta_3 \text{Coal}_t + \varepsilon_t \quad (2.9)$$

with $EUARET$ as the dependent variable, $\{\text{BRENTRET}, \text{NGASRET}, \text{COALRET}\}$ as independent variables, α as the constant, and ε_t as the error term.⁶ This regression can be computed with R based on Table 2.6.

⁶Note that we do not consider here econometric models where the variance of the processes is not constant, which will be dealt with in the next chapter.

Table 2.6 R Code: Linear Regression Model with Energy Variables

```
1 path<-"C:/"
2 setwd(path)
3 library(stats)
4 data=read.csv("data_chapter2.csv",sep=",")
5 attach(data)
6 eua=data[,2]
7 brent=data[,5]
8 gas=data[,6]
9 coal=data[,7]
10 modelenergy<-lm(eua~brent+gas+coal)
11 summary(modelenergy)
12 layout(matrix(1:4,2,2))
13 plot(modelenergy)
14 acf(residuals(modelenergy))
15 acf(residuals(modelenergy),type='partial')
```

Table 2.7 R Output: Linear Regression Model with Energy Variables

```
Call:
lm(formula = eua ~ brent + gas + coal)

Residuals:
      Min       1Q   Median       3Q      Max
-0.08979 -0.01512 -0.00064  0.01309  0.55154

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.000606   0.001561   0.388   0.6980
brent        0.098255   0.052959   1.855   0.0641 .
gas          0.068477   0.035243   1.943   0.0526 .
coal        -0.134923   0.067990  -1.984   0.0477 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.03589 on 525 degrees of freedom
Multiple R-squared:  0.02296,    Adjusted R-squared:  0.01738
F-statistic: 4.113 on 3 and 525 DF,  p-value: 0.006704
```

This code returns the output reproduced in Table 2.7. We observe that the three energy variables considered as significant in explaining carbon price changes at usual statistical levels.⁷ The coefficient estimates for the brent and natural gas variables is positive and significant at the 10% level. The coefficient estimate for the coal variable is *negative*—as expected due to its carbon-

⁷The user may test other specifications, for instance by introducing various lags for the dependent and independent variables.

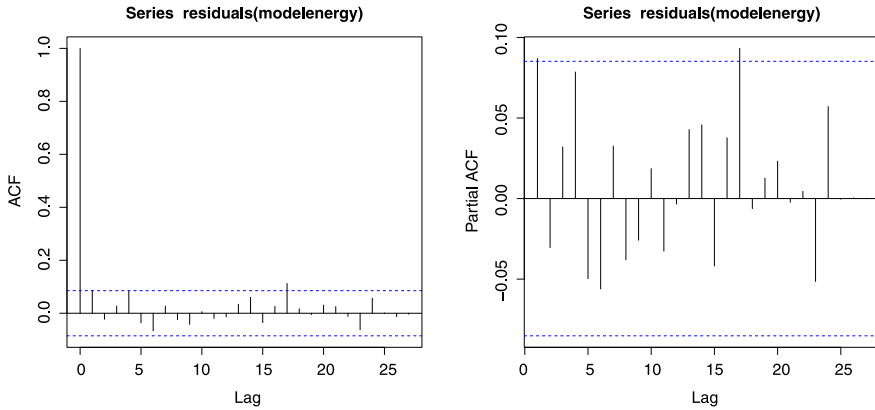


Fig. 2.8 Autocorrelation and partial-autocorrelation functions for the residuals from the model estimated in Eq. (2.9)

intensive content—and significant at the 5% level. Therefore, we are able to verify in this example that the use of fuels such as brent and natural gas has a positive impact on the carbon price. Higher demand for energy will translate into more fuel use, higher prices for brent and natural gas, and increased demand for CO₂ allowances. Conversely, the use of coal has a negative impact on the carbon price. As the more carbon-intensive input to produce energy, when the price of coal rises, agents need to reduce their consumption of coal, which leads to decreased demand for CO₂ allowances. The Adjusted R-Squared is low (0.0173), which means that the explanatory power of this regression can be improved by adding other relevant independent variables, as it will be detailed later in this chapter. The p -value of the F -test statistic (0.0067) shows that the joint significance of the results is accepted at the 1% level.

Lines 12 to 15 allow to check the residuals of the regression. We only reproduce the ACF and PACF below in Fig. 2.8. We cannot detect any systematic pattern in the residuals, which stay safely within the confidence intervals, and hence we conclude that the errors are not autocorrelated for this regression.

Next, let us explore the relationship between the carbon price and electricity variables.

2.2.3 Electricity Variables

Depending on the share of coal and gas in their electricity mix, power producers may benefit from the opportunity to switch from coal to gas depending on the price of the carbon price in order to minimize the electricity production cost.⁸ The opportunity to switch provides an interesting solution for power generators to reduce their

⁸Note we consider here the switching between coal and gas to produce one unit of electricity. Oil is mostly used to meet high peak demand, especially in winter. Thus, oil is unlikely to interfere with coal and gas switching in the European system. Besides, gas and coal are the cheapest alternatives, while oil has encountered a high level of volatility during the recent period.

emissions at low cost. In order to benefit from these cheap abatement opportunities, electricity generators need to compare the CO₂ price and marginal abatement costs. It may be cheaper to switch for a less carbon-intensive fuel (such as gas) instead of using coal and buying permits. That is why, in this section, we describe the basic principle behind fuel-switching for power producers.

2.2.3.1 Fuel-Switching Behavior

In the power sector, electricity prices are determined by the marginal generation technology. Different generation units are ranked by marginal costs from the cheapest technology to the most expensive one.⁹ The introduction of a carbon cost through tradable permits changes the carbon intensity of power generation technologies, and modifies the competitiveness of power plants. Through the introduction of high carbon costs, gas-fired power plants—which are more expensive but less CO₂-intensive than coal-fired power plants—may become more profitable than coal-fired power plants. The price of carbon that makes the two technologies equally attractive is called the ‘switching point’.¹⁰

Basic Principle Without carbon costs, the marginal cost of producing electricity is given by the ratio between fuel costs and the efficiency of the plant. It may be calculated by using the plants efficiencies [23]:

$$MC = \frac{FC}{\eta} \quad (2.10)$$

with MC the marginal cost, FC the fuel cost, and η the efficiency of the plant. With carbon costs, the marginal cost for each plant contains the emission factor which depends on the fuel burnt:

$$MC = \frac{FC}{\eta} + \frac{EF}{\eta} \times EC \quad (2.11)$$

with EF the emission factor, and EC the emission cost. The switching point between a given coal-fired plant and a given gas-fired power plant may be computed as the emission cost which leads to $MC_{ngas} = MC_{coal}$. It represents the carbon cost that leads to a switch between two plants in the merit order. This price depends on each plant’s fuel cost, efficiency and emission factors:

$$EC_{switch} = \frac{\eta_{coal} \times FC_{ngas} - \eta_{ngas} \times FC_{coal}}{\eta_{ngas} \times EF_{coal} - \eta_{coal} \times EF_{ngas}} \quad (2.12)$$

If the carbon price is lower than the switching point, electricity generation through coal is more profitable than gas.¹¹

⁹This ranking is called ‘merit order’, and depends on several parameters such as fuel prices, plant efficiencies and carbon intensity.

¹⁰We do not include in the analysis the capital and operations and maintenance costs of coal versus natural gas. Hence, we aim at capturing the *short-term* effect of introducing emissions trading on power producers’ fuel-switching behaviour. A longer term analysis requires an estimation of fuel substitution with additional costs associated to retro-fit.

¹¹Also note that the potential for fuel-switching is very dependent on the load. Indeed, at full load, during winter peak-hours for instance, all the plants are running so that no opportunity to

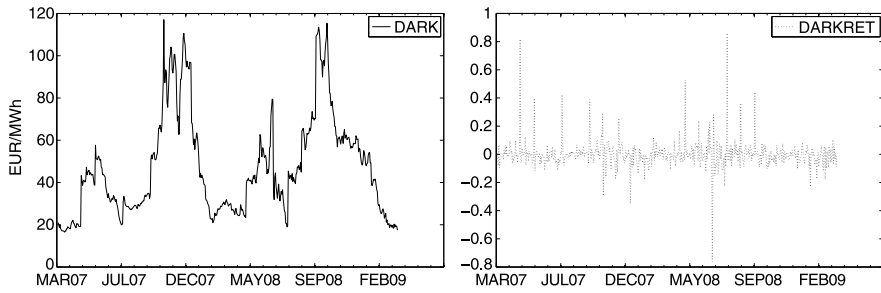


Fig. 2.9 Clean Dark Spread: Raw data (left panel) and logreturns (right panel) from March 09, 2007 to March 31, 2009

Clean Dark Spread, Clean Spark Spread and Switch Price Power operators pay close attention to the Dark and Spark spreads, as well as to the difference between them. The Dark spread represents the theoretical profit that a coal-fired power plant makes from selling a unit of electricity, having purchased the fuel required to produce that unit of electricity. The Spark spread refers to the equivalent for natural gas-fired power plants. With the introduction of carbon costs, the Dark and Spark spreads need to be corrected by EUA prices, and thus become respectively the Clean Dark and Clean Spark spreads. The Switch price represents the threshold for the carbon price *above* which it becomes profitable for an electric power producer to switch from coal to natural gas, and *below* which it is beneficial to switch from natural gas to coal. This switching price is more sensitive to natural gas price changes than to coal prices changes [36]. Together, these three profitability indicators are used to determine the preferred fuel used for power generation. Now, let us describe in more details these electricity variables selected to study the effect of power producers' fuel-switching behavior on the carbon price.

Clean Dark Spread First, the Clean Dark Spread (*clean dark*, expressed in Euro/MWh) represents the difference between the price of electricity at peak hours (*elec*) and the price of coal (*coal*) used to generate that electricity, corrected for the energy output of the coal plant and the costs of CO₂ (p_t):

$$clean\ dark = elec - \left(coal \times \frac{1}{\rho_{coal}} + p_t \times EF_{coal} \right) \quad (2.13)$$

with ρ_{coal} the net thermal efficiency of a conventional coal-fired plant (i.e. 35% according to Reuters), and EF_{coal} the CO₂ emissions factor of a conventional coal-fired power plant (i.e. 0.95 tCO₂/MWh according to Reuters). The Clean Dark Spread is shown in Fig. 2.9.

switch exists. The switch can only occur if coal-plants are running while some gas-fired plants are available to replace them. The best opportunities occur when the load is relatively low and mostly met by coal-fired-plants, i.e. during weekends, nights and summers. Then, with adequate economic incentives, available gas-fired units may be switched. Consequently, the possibility of fuel-switching varies throughout the year depending on the season (winter or summer), the time of the week (day-of-week or week-end effects), and the period of the day (day or night).

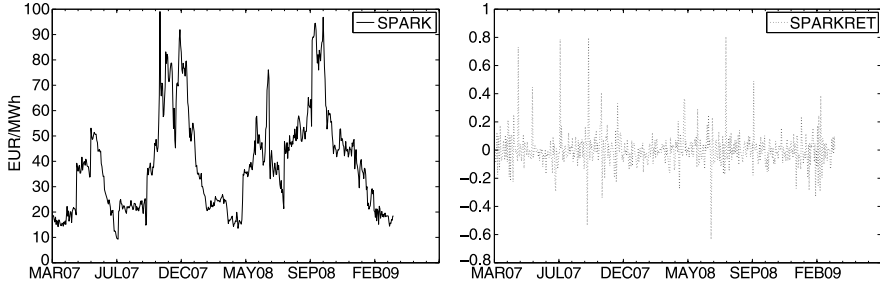


Fig. 2.10 Clean Spark Spread: Raw data (*left panel*) and logreturns (*right panel*) from March 09, 2007 to March 31, 2009

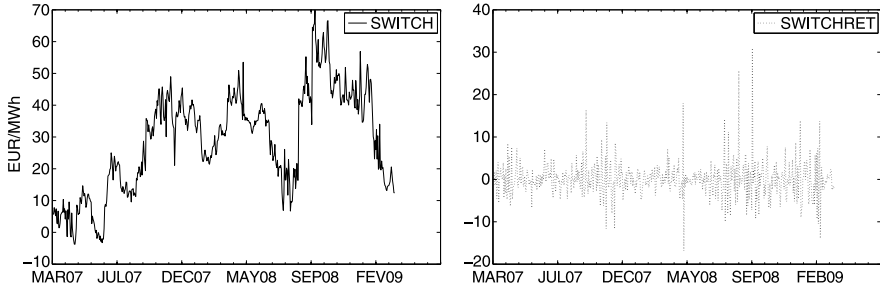


Fig. 2.11 Switch Price: Raw data (*left panel*) and logreturns (*right panel*) from March 09, 2007 to March 31, 2009

Clean Spark Spread Second, the Clean Spark Spread (*clean spark*, expressed in Euro/MWh) represents the difference between the price of electricity at peak hours and the price of natural gas (*ngas*) used to generate that electricity, corrected for the energy output of the gas-fired plant and the costs of CO₂:

$$clean\ spark = elec - \left(ngas \times \frac{1}{\rho_{ngas}} + p_t \times EF_{ngas} \right) \quad (2.14)$$

with ρ_{ngas} the net thermal efficiency of a conventional gas-fired plant (i.e. 49% according to Reuters), and EF_{ngas} the CO₂ emissions factor of a conventional coal-fired power plant (i.e. 0.41 tCO₂/MWh according to Reuters). The Clean Spark Spread is shown in Fig. 2.10.

Switch Price Third, the Switch Price (*switch*, expressed in Euro/MWh) represents the shadow price that allows equalizing the Clean Dark and Clean Spark spreads:

$$switch = \frac{cost_{ngas}/MWh - cost_{coal}/MWh}{tCO_{2coal}/MWh - tCO_{2ngas}/MWh} \quad (2.15)$$

with $cost_{ngas}$ the production cost of one MWh of electricity based on net CO₂ emissions of gas (expressed in EUR/MWh), $cost_{coal}$ the production cost of one MWh of electricity based on net CO₂ emissions of coal (expressed in Euro/MWh), tCO_{2coal}

Table 2.8 Cross-correlations between carbon (EUA) and electricity (DARK, SPARK, SWITCH) variables in logreturns transformation

	EUARET	DARKRET	SPARKRET	SWITCHRET
EUARET	1			
DARKRET	0.0687	1		
SPARKRET	−0.0455	0.1775	1	
SWITCHRET	0.1617	0.3075	−0.3586	1

the emissions factor (expressed in tCO_2/MWh) of a conventional coal-fired plant, and tCO_{2gas} the emissions factor (expressed in tCO_2/MWh) of a conventional gas-fired plant. The switch price is shown in Fig. 2.11. As long as the carbon price is below this switching price, coal plants are more profitable than gas plants—even after taking carbon costs into account.

Similarly to energy variables, we verify in Table 2.8 that the cross-correlations between the carbon price and electricity variables (taken in logreturns) do not exceed 0.6 in absolute value. Then, we can proceed to the regression analysis of carbon price drivers with electricity variables.

2.2.3.2 Regression Analysis

We run the following regression:

$$y_t = \alpha + \phi y_{t-1} + \beta_4 \text{Clean Dark}_t + \beta_5 \text{Clean Spark}_t + \beta_6 \text{Switch}_t + \varepsilon_t \quad (2.16)$$

with ϕ the parameter for the AR(1) process, and β_4 to β_6 the coefficient estimates for, respectively, *DARKRET*, *SPARKRET* and *SWITCHRET*. This regression can be estimated by using the R code in Table 2.9.

This code yields to the output reproduced in Table 2.10.

Besides the influence of the AR(1) process (significant at the 1% level), we uncover in this example the statistically significant impact of the Clean Spark Spread (*spark*) on carbon price changes at the 10% level. Neither the Clean Dark Spread, nor the Switch Price carry explanatory power in the model estimated according to Eq. (2.16). However, note that the sign of the β_4 coefficient obtained for the Clean Dark Spread (*dark*) is *negative*, which is consistent with the negative sign for the coal variable identified in Eq. (2.9). In addition, the user may experiment various lag specifications for electricity variables.

Lines 14–15 plot the ACF and PACF of the residuals from the electricity model in Eq. (2.16). By looking at Fig. 2.12, we conclude that the residuals of this regression are not autocorrelated. The p -value of the F -test statistic also confirms the joint significance of this regression.

Note that the factors which influence the fuel-switching behavior of power producers are further analyzed in Chap. 5.

Having detailed the channels through which energy prices are deemed to affect the price path of carbon, we consider in the next section a third category of carbon price drivers: extreme weather events.

Table 2.9 R Code: Linear Regression Model with Electricity Variables

```

1  path<-"C:/"
2  setwd(path)
3  library(dynlm)
4  data=read.csv("data_chapter2.csv",sep=",")
5  attach(data)
6  eua=data[,2]
7  dark=data[,8]
8  spark=data[,9]
9  switch=data[,10]
10 modelelectricity<-dynlm(formula=eua~L(eua)+dark+spark+switch)
11 summary(modelelectricity)
12 layout(matrix(1:4,2,2))
13 plot(modelelectricity)
14 acf(residuals(modelelectricity))
15 acf(residuals(modelelectricity),type='partial')

```

Table 2.10 R Output: Linear Regression Model with Electricity Variables

Call:

```
dynlm(formula = eua ~ L(eua) + dark + spark + switch)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-1.268e-17	-6.167e-19	-1.168e-19	4.896e-19	2.937e-17

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.000e+00	9.685e-20	0.000e+00	1.0000
L(eua)	1.000e+00	2.679e-18	3.733e+17	<2e-16 ***
dark	-1.420e-18	1.089e-18	-1.304e+00	0.1930
spark	1.498e-18	8.746e-19	1.713e+00	0.0873 .
switch	4.100e-20	2.754e-20	1.489e+00	0.1371

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.227e-18 on 524 degrees of freedom

Multiple R-squared: 1, Adjusted R-squared: 1

F-statistic: 3.489e+34 on 4 and 524 DF, p-value: < 2.2e-16

2.3 Extreme Weather Events

The influence of temperatures and weather events needs also to be accounted for when examining the carbon price drivers. We explain below the rationale behind these effects, along with an example.

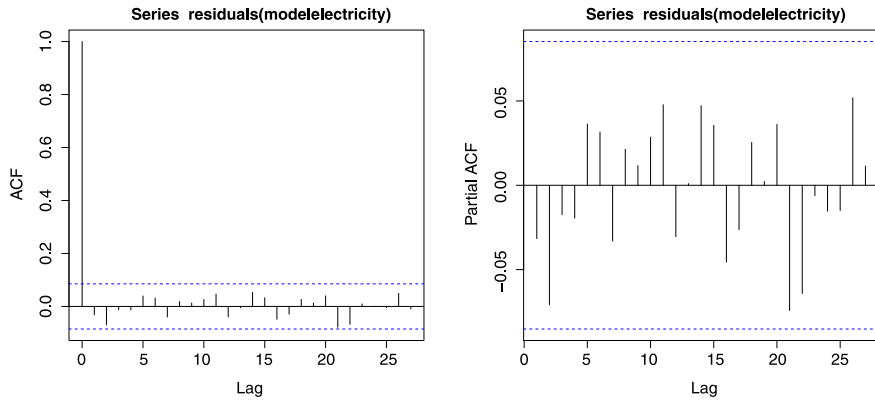


Fig. 2.12 Autocorrelation and partial-autocorrelation functions for the residuals from the model estimated in Eq. (2.16)

2.3.1 Relationship Between Temperatures and Carbon Prices

Taken together, cold and hot temperatures constitute the most important dimension of weather [45].¹² In turn, weather conditions are expected to impact the price path of carbon insofar as they influence energy demand. For instance, cold winters yield to increased use of heating, and thus extra need for power generation. Conversely, hot summers yield to extra need for air conditioning, which also increases electricity production. More power production will be achieved by more fuel use (associated with CO₂ emissions), and in fine there will be a need for more CO₂ allowances (with a positive effect on the CO₂ price). Therefore, we may consider a broad European temperatures index as a suitable carbon price driver.

To illustrate our point, we detail the functioning of the Metnext Weather index.¹³ This national business-climate index is defined as the average daily temperature of the regions making up the country, weighted by the population of these regions. This methodology allows to derive a good approximation of the weight of regional economic activity. The index, expressed in Degree Celsius, is computed for eighteen countries¹⁴ as follows:

$$\theta = \frac{\sum_{i=1}^N p_i \times \theta_i}{\sum_{i=1}^N p_i} \quad (2.17)$$

with N the number of regions in the country under consideration, p_i the population of region i , and θ_i the average temperature of region i during the month under consideration.

¹²Due to data limitations (and lack of availability at the European level), we do not consider here other potential weather events linked to rainfall or wind.

¹³See the website at the following address: <http://www.weatherindices.com/index>.

¹⁴Austria, Belgium, Germany, Denmark, Spain, Finland, France, United-Kingdom, Hungary, Ireland, Italy, the Netherlands, Norway, Poland, Portugal, Sweden, Slovakia and Slovenia.

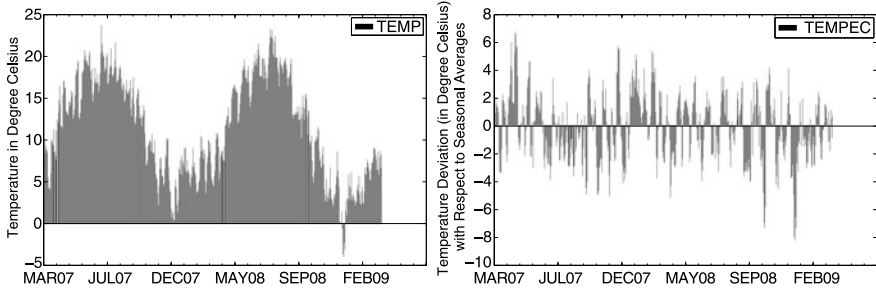


Fig. 2.13 Weather Events: European Temperatures Index (*left panel*) and Temperatures Deviation from Seasonal Average (*right panel*) in Degree Celsius from March 09, 2007 to March 31, 2009

Then, the CDC Climate Research¹⁵ has extended this methodology to take into account the specificities of the carbon market. Their European temperatures index is equal to the average of the national temperature indices θ provided by Metnext Weather for the eighteen countries, weighted by the weight of each country in the total volume of distributed allowances:

$$T = \frac{\sum_{j=1}^4 Q_j \times \theta_j}{\sum_{j=1}^4 Q_j} \quad (2.18)$$

with T the monthly index, Q_j the number of allowances allocated by country j in its National Allocation Plan, and θ_j the national temperatures index of country j . An example of this European Temperatures Index (expressed in Degree Celsius) is displayed in the left panel of Fig. 2.13.

However, it is worth highlighting that the impact of temperatures on carbon prices is essentially nonlinear, i.e. it is possible to identify econometrically statistically significant effect of weather events only *above* or *below* a given threshold [2]. That is why, in the right panel of Fig. 2.13, we also reproduce temperatures deviation from decennial seasonal averages (expressed in Degree Celsius). The main insight behind this plot is that *unanticipated* temperatures events only can have an effect on carbon prices. If temperatures are conform to seasonal averages, then market participants (brokers, analysts, investors, ...) can properly anticipate them.

That is why we do not propose in the next section a regression analysis based on either the temperatures index, or the deviation from seasonal averages. These variables are not powerful enough (in statistical terms) to carry explanatory power concerning carbon price changes. Other econometric variables need to be constructed in order to capture the effects of extreme weather events.

¹⁵See the website at the following address: <http://www.cdcclimat.com>.

Table 2.11 R Code: Linear Regression Model with Extreme Weather Events

```

1  path<-"C:/"
2  setwd(path)
3  library(stats)
4  data=read.csv("data_chapter2.csv",sep=",")
5  attach(data)
6  eua=data[,2]
7  tempcold=data[,11]
8  temphot=data[,12]
9  modelweather<-lm(eua~tempcold+temphot)
10 summary(modelweather)
11 layout(matrix(1:4,2,2))
12 plot(modelweather)
13 acf(residuals(modelweather))
14 acf(residuals(modelweather),type='partial')

```

2.3.2 Empirical Application

For the purpose of our empirical application, let us consider the following regression:

$$y_t = \alpha + \beta_7 Tempcold_t + \beta_8 Temphot_t + \varepsilon_t \quad (2.19)$$

where $Tempcold_t$ is a dummy variable capturing the influence of cold temperatures (it is equal to one when the temperatures index in a given month is below decennial seasonal averages by -1.97 Degree Celsius), and $Temphot_t$ is a dummy variable capturing the influence of hot temperatures (it is equal to one when the temperatures index in a given month is above decennial seasonal averages by 1.47 Degree Celsius). As already described in Sect. 2.1.1, dummy variables appear as suitable tools for the investigation of weather effects on carbon prices. This regression may be estimated by using R in Table 2.11.

The results are shown in Table 2.12.

We may observe that the β_7 and β_8 coefficients, capturing the effects of $Tempcold_t$ and $Temphot_t$ respectively, are statistically significant at the 5% level. Therefore, we are able to confirm in this example that extreme temperatures events, i.e. temperatures events *above* or *below* decennial seasonal averages, have a statistically significant effect on carbon prices by following the economic logic explained in Sect. 2.3.1.

The p -value of the F -test statistic confirms that the joint significance of the results is accepted. As shown by the ACF and PACF functions in Fig. 2.14, we can also accept the null hypothesis that residuals of the regression are not autocorrelated.

Table 2.12 R Output: Linear Regression Model with Extreme Weather Events

```
Call:
lm(formula = eua ~ tempcold + temphot)

Residuals:
    Min       1Q   Median       3Q      Max
-0.10435 -0.01521 -0.00075  0.01435  0.54939

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.008816   0.004597  -1.918   0.0557 .
tempcold     0.009256   0.004621   2.003   0.0457 *
temphot      0.009561   0.004612   2.073   0.0386 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.03611 on 526 degrees of freedom
Multiple R-squared:  0.009094,    Adjusted R-squared:  0.005327
F-statistic: 2.414 on 2 and 526 DF,  p-value: 0.09047
```

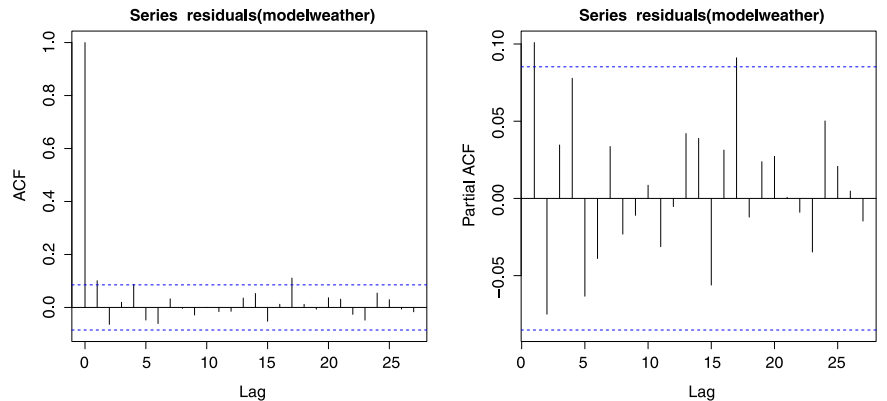


Fig. 2.14 Autocorrelation and partial-autocorrelation functions for the residuals from the model estimated in Eq. (2.19)

To conclude this chapter, we invite the reader to combine all the carbon price drivers considered here by using the linear regression model, in the spirit of the practical examples developed above, or by using GARCH models as introduced in the next chapter. As shown by previous academic literature [2], the influence of such drivers (mainly energy variables and extreme temperatures events) varies depending on the period under consideration and the influence of institutional decisions (which may also be accounted for by considering sub-samples).

Box 2.5 (Homoskedasticity Tests) This chapter has not dealt with the notion of non-constant variance (i.e. heteroskedasticity), which is gradually introduced in Chap. 3.

We briefly present below the main statistical tests to detect the presence of heteroskedasticity in the residuals of regression models.

According to the White test, a general test of homoskedasticity may be written as:

$$\hat{\varepsilon}_t^2 = a_0 + a_1 X_{t-1} + b_1 X_{t-1}^2 + \cdots + a_p X_{t-p} + b_p X_{t-p}^2 + v_t \quad (2.20)$$

with $\hat{\varepsilon}_t$ the estimated residuals, and X_{t-p} the lagged endogenous variable. The test is based on the Lagrange multiplier (LM) with T the number of observations, and R^2 the R-squared of Eq. (2.20). If $TR^2 < \chi^2(2p)$, the null hypothesis of homoskedasticity is accepted (see Hamilton (1996, [33]) for more details).

According to the Engle ARCH test, the null hypothesis of homoskedasticity can also be tested by running the following regression:

$$\hat{\varepsilon}_t^2 = \alpha_0 + \sum_{i=1}^l \alpha_i \hat{\varepsilon}_{t-i}^2 \quad (2.21)$$

If $TR^2 < \chi^2(l)$, the null hypothesis of homoskedasticity is accepted.

Homoskedasticity tests of the residuals can be performed in R with the following commands:

```
1 library(lmtest)
2 library(vars)
3 model<-lm(eua~ar(1)+ar(p))
4 bptest(model,~ar(1)*ar(p)+I(ar(1)^2)+I(ar(p)^2))
5 model<-VAR(eua,p=2)
6 arch(model)
```

Lines 1 and 2 load the relevant libraries. Lines 3 and 4 compute the White test as a special case of the `bptest()` command, by including all regressors and the squares/cross-products in the auxiliary regression. Lines 5 and 6 compute the Engle ARCH test in the framework of a $\text{VAR}(p)$ (see Chap. 4).

Appendix: BEKK MGARCH Modeling with CO₂ and Energy Prices

Based on the Baba-Engle-Kraft-Kroner ([11, 30], BEKK) specification of the Multivariate GARCH (MGARCH) model, we highlight in this section the transmission of price volatility among carbon (EUA) and energy (oil, gas, coal) markets. Note that the univariate GARCH modelling framework is detailed in Chap. 3. The data

for this section is available at: http://sites.google.com/site/jpchevallier/publications/books/springer/data_chapter2_appendix.csv.

The BEKK MGARCH Model The class of multivariate GARCH models that we study stems from the contributions of Bollerslev, Engle and Wooldridge ([11], 1988), who provided with the VEC-GARCH model a straightforward extension of univariate GARCH models. We examine more particularly the following BEKK MGARCH model [30]:

$$H_t = CC' + \sum_{j=1}^q \sum_{k=1}^K A'_{kj} r_{t-j} r'_{t-j} A_{kj} + \sum_{j=1}^p \sum_{k=1}^K B'_{kj} H_{t-j} B_{kj} \quad (2.22)$$

where A_{kj} , B_{kj} , and C are $N \times N$ parameter matrices, and C is lower triangular to ensure the positive definiteness of H_t . Note the BEKK model is covariance stationary if and only if the eigenvalues of $\sum_{j=1}^q \sum_{k=1}^K A_{kj} \otimes A_{kj} + \sum_{j=1}^p \sum_{k=1}^K B_{kj} \otimes B_{kj}$ are less than one in modulus, with $\otimes$ the notation for Kronecker products. Due to the computational burden involved by the estimation of a full BEKK model,¹⁶ we restrict the number of parameters by implementing the following “diagonal BEKK” MGARCH model:

$$H_t = CC' + A' r_{t-1} r'_{t-1} A + DE[A' r_{t-1} r'_{t-1} A \mid \mathfrak{F}_{t-2}] D \quad (2.23)$$

In Eq. (2.23), we now model the conditional variances and covariances of certain linear combinations of the vector of price returns r_t .

Estimation with R The R code to estimate the BEKK MGARCH model is given in Table 2.13. Note the MGARCH BEKK package for R may be downloaded at: <http://www.quantmod.com/download/mgarchBEKK/>.

Table 2.13 R Code: Estimating the BEKK MGARCH model

```

1  path<-"C:/ "
2  setwd(path)
3  library(mgarchBEKK)
4  data=read.csv("data_chapter2_appendix.csv", sep=", ")
5  attach(data)
6  eua=data[,2]
7  oil=data[,3]
8  gas=data[,4]
9  coal=data[,5]
10 mgarch.mat<-data.frame(eua,oil,gas,coal)
11 model.BEKK<-mvBEKK.est(mgarch.mat,order=c(1,1,1,1),
    params=NULL)
12 mvBEKK.diag(model.BEKK)

```

¹⁶As the number of parameters $(p+q)KN^2 + N(N+1)/2$ increases, it may be difficult to obtain convergence during the estimation.

Table 2.14 R Output: Estimating the BEKK MGARCH model

```

Number of estimated series : 4
Length of estimated series : 529
Estimation Time           : 7.7362
Total Time                 : 7.760683
BEKK order                 : 1 1 1 1
Eigenvalues                : 1.371115 1.017605 0.9884797 0.72346 0.6930659 0.5845497 0.506614
                           : 0.4460167 0.3941953 0.2683696 0.1986257 0.08505935 0.05234043
                           : 0.03286894 0.007029388 0.004263158
aic                        : -5351.701
unconditional cov. matrix : 0.001148309 0.0001154143 -0.0006690489 0.0001950053 0.0001154143
                           : 0.0006749642 -0.0004209732 -0.0001267162 -0.0006690489 -0.0004209732
                           : 0.001150107 9.731776e-05 0.0001950053 -0.0001267162 9.731776e-05
                           : 0.0001509592
var(resid 1 )              : 0.9853412
mean(resid 1 )             : 0.02929001
var(resid 2 )              : 0.956688
mean(resid 2 )             : -0.001323343
var(resid 3 )              : 1.045084
mean(resid 3 )             : 0.01247064
var(resid 4 )              : 1.034191
mean(resid 4 )             : 0.05121381
Estimated parameters       :

C estimates:
      [,1]      [,2]      [,3]      [,4]
[1,] -0.0181858 -0.002252538 0.017789029 -2.384224e-03
[2,] 0.0000000 0.014754446 -0.022988227 -6.830455e-03
[3,] 0.0000000 0.000000000 0.007573896 2.210108e-07
[4,] 0.0000000 0.000000000 0.000000000 -1.180576e-04

ARCH estimates:
      [,1]      [,2]      [,3]      [,4]
[1,] 0.7660670 0.07154282 0.27820714 0.27219474
[2,] 0.2332687 0.33612697 -0.03536674 0.02553457
[3,] -0.2442194 0.01900365 0.01417112 0.22302539
[4,] 0.1541698 0.05541739 0.05950522 0.18045794

GARCH estimates:
      [,1]      [,2]      [,3]      [,4]
[1,] -0.1066946471 -0.456940766 -0.56919659 -0.01460560
[2,] 0.5081535812 -0.141011118 0.58304368 -0.27584249
[3,] -0.0004665412 0.461722817 0.42903780 -0.01917917
[4,] 0.0311903261 -0.003331396 0.02776824 -0.70484255

asy.se.coef      :

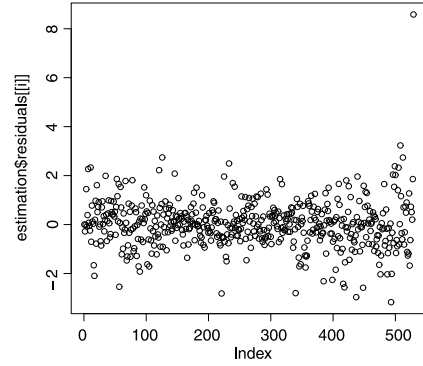
C estimates, standard errors:
      [,1]      [,2]      [,3]      [,4]
[1,] 0.001856379 0.013672040 0.012979851 0.004585833
[2,] 0.000000000 0.004089436 0.005244723 0.001519628
[3,] 0.000000000 0.000000000 0.008788042 0.007997546
[4,] 0.000000000 0.000000000 0.000000000 0.008027800

ARCH estimates, standard errors:
      [,1]      [,2]      [,3]      [,4]
[1,] 0.07108107 0.11079524 0.10873442 0.05337258
[2,] 0.06340028 0.05735820 0.06200331 0.05674444
[3,] 0.01243639 0.03171205 0.05404650 0.01870268
[4,] 0.06916141 0.06702569 0.05706629 0.06795449

GARCH estimates, standard errors:
      [,1]      [,2]      [,3]      [,4]
[1,] 0.10369959 0.13957939 0.18168679 0.11921919
[2,] 0.07110973 0.08714015 0.18288946 0.11336719
[3,] 0.25998745 0.06305122 0.09347202 0.04677360
[4,] 0.24299070 0.06075734 0.38037655 0.09695227

```

Fig. 2.15 Residual series for the BEKK MGARCH model estimated in Eq. (2.23)



Lines 1 to 10 load the relevant library and data. Line 11 performs the estimation of the BEKK MGARCH model, which returns the output shown in Table 2.14.

The coefficients for the variance-covariance equations are generally significant for own- and cross-innovations, and significant for own- and cross-volatility spillovers in the individual price series of oil, gas, coal and CO₂, indicating the presence of strong ARCH and GARCH effects. In evidence, most of the estimated ARCH and GARCH coefficients are significant at the 1% level.

Line 12 provides the graph of the residuals, as pictured in Fig. 2.15. We cannot identify any pattern in the residual series, therefore we can conclude that the BEKK MGARCH model for carbon and energy markets is well-specified (without evidence of autocorrelation in the residuals).

The interested reader may refer to Chevallier (2012, [14]) for an extension of this analysis to constant conditional correlation ([10], CCC) and dynamic conditional correlation ([29, 31], DCC) MGARCH models. Also, the DCC MGARCH model has been applied to the relationship between EUAs and CERs [13].

Problems

Problem 2.1 (Unit Root Tests for Carbon Prices)

- Consider the time-series in Fig. 2.16: do you observe spikes (upside peaks followed by downside jumps)? are the trajectories formed by random oscillations? do the price series evolve around a random trend? does volatility seem higher and spikes more frequent during some specific periods?
- Consider the time-series in Fig. 2.17: do you observe correlation peaks following a specific pattern? which prices between day d and day $d - n$ seem more correlated than prices with other lags?
- Consider the Tables 2.15 and 2.16, which report the ADF, PP, and KPSS tests: what do you conclude? for which time-series can H_0 be rejected? for which time-series can you not reject H_0 ? detail the methodology to transform non-stationary variables to stationary, and the possible bias induced if the process is TS or DS.

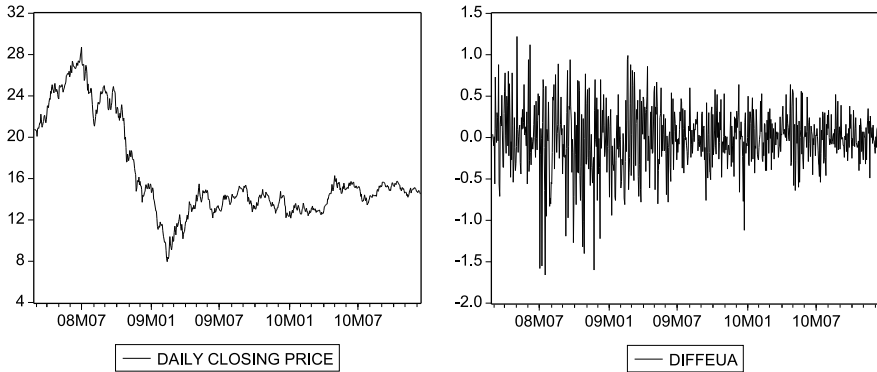


Fig. 2.16 Raw time-series (*left panel*) and logreturns (*right panel*) of the ECX EUA Futures Contract

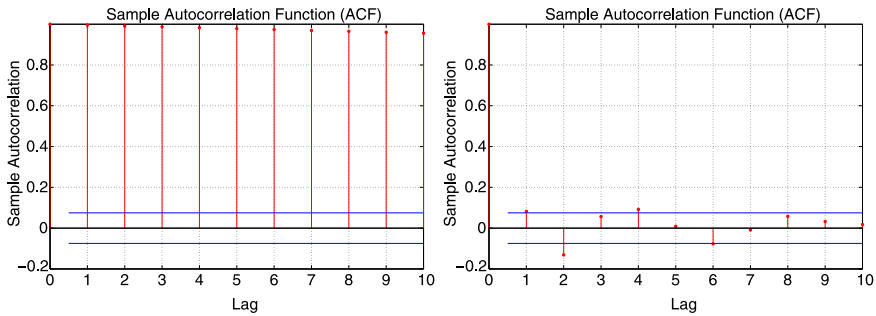


Fig. 2.17 ACF functions of the ECX EUA Futures contract in raw (*left panel*) and logreturn (*right panel*) forms

Problem 2.2 (Calibration of Mean-Reversion Models for Carbon Prices) The simplest mean-reversion model is the so-called AR(1) model:

$$x_{t+1} = \rho x_t + \beta + e_{t+1} \quad (2.24)$$

where the (e_t) are i.i.d. with law $N(0, \sigma^2)$.

The calibration proceeds in two steps:

1. the coefficients ρ and β are determined by OLS regression of x_{t+1} on x_t ;
2. σ is computed as the standard deviation of the residuals of the regression.
 - (a) How would you calibrate this model to the CO₂ price series?
 - (b) Consider the results presented in Table 2.17: what do you observe?
 - (c) Consider the diagnostic tests presented in Table 2.18: what can you conclude concerning the hypothesis H_0 that the residuals are uncorrelated using the Box-Pierce test? concerning the hypothesis H_0 that the residuals follow a Gaussian law using the Jarque-Bera test? concerning the hypothesis H_0 that the residuals present heteroskedasticity using the Engle ARCH test?

Table 2.15 Unit root tests for the EUA_t variable

Null Hypothesis: EUA has a unit root

Exogenous: None

Lag Length: 0 (Automatic based on SIC, MAXLAG = 19)

	t -Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-0.9301	0.3135
Test critical values:		
1% level	-2.5682	
5% level	-1.9412	
10% level	-1.6164	

*MacKinnon (1996, [40]) one-sided p -values

Null Hypothesis: EUA has a unit root

Exogenous: None

Bandwidth: 1 (Newey-West using Bartlett kernel)

	Adj. t -Stat	Prob.*
Phillips-Perron test statistic	-0.9206	0.3174
Test critical values:		
1% level	-2.5682	
5% level	-1.9412	
10% level	-1.6164	

*MacKinnon (1996, [40]) one-sided p -values

Null Hypothesis: EUA is stationary

Exogenous: Constant

Bandwidth: 22 (Newey-West using Bartlett kernel)

	LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic	1.5748
Asymptotic critical values*:	
1% level	0.7390
5% level	0.4630
10% level	0.3470

*Kwiatkowski-Phillips-Schmidt-Shin (1992, [39])

Note: ADF and PP: Model 1 (without intercept or trend) has been chosen. KPSS: Model 2 without trend has been chosen

Table 2.16 Unit root tests for the $D(EUA_t)$ variableNull Hypothesis: $D(EUA)$ has a unit root

Exogenous: Constant

Lag Length: 1 (Automatic based on SIC, MAXLAG = 19)

	t -Statistic	Prob.*
Augmented Dickey-Fuller test statistic	−20.4963	0.0000
Test critical values:		
1% level	−3.4393	
5% level	−2.8653	
10% level	−2.5688	

*MacKinnon (1996, [40]) one-sided p -valuesNull Hypothesis: $D(EUA)$ has a unit root

Exogenous: Constant

Bandwidth: 2 (Newey-West using Bartlett kernel)

	Adj. t -Stat	Prob.*
Phillips-Perron test statistic	−24.9767	0.0000
Test critical values:		
1% level	−3.4393	
5% level	−2.8653	
10% level	−2.5688	

*MacKinnon (1996, [40]) one-sided p -valuesNull Hypothesis: $D(EUA)$ is stationary

Exogenous: Constant

Bandwidth: 1 (Newey-West using Bartlett kernel)

	LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic	0.1408
Asymptotic critical values*:	
1% level	0.7390
5% level	0.4630
10% level	0.3470

*Kwiatkowski-Phillips-Schmidt-Shin (1992, [39])

Note: ADF and PP: Model 1 (without intercept or trend) has been chosen. KPSS: Model 2 without trend has been chosen

Table 2.17 Estimation of the mean-reversion model

Dependent Variable: DIFFEUA				
Method: Least Squares				
Sample (adjusted): 2/28/2008 12/09/2010				
Included observations: 711 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	−0.0082	0.0143	−0.5742	0.5660
DIFFEUA(-1)	0.0620	0.0374	1.6564	0.0981
R-squared	0.0038	Mean dependent var		−0.0087
Adjusted R-squared	0.0024	S.D. dependent var		0.3840
S.E. of regression	0.3836	Akaike info criterion		0.9244
Sum squared resid	104.3328	Schwarz criterion		0.9372
Log likelihood	−326.6300	F-statistic		2.7438
Durbin-Watson stat	1.9850	Prob(F-statistic)		0.0980

Table 2.18 Diagnostic tests of the mean-reversion model

Diagnostic tests	
Box-Pierce test	0.8470
Jarque-Bera test	0.0001
Engle ARCH test	0.0034

Note: The Box-Pierce test is computed with 20 lags. The p -value of the Jarque-Bera test is given. The Engle ARCH test is computed with one lag

- (d) How would you correct the potential mis-specification problems in the model estimated based on your answer to question (c)?

References

1. Alberola E, Chevallier J (2009) European carbon prices and banking restrictions: evidence from Phase I (2005–2007). *Energy J* 30:51–80
2. Alberola E, Chevallier J, Cheze B (2008) Price drivers and structural breaks in European carbon prices 2005–07. *Energy Policy* 36:787–797
3. Alberola E, Chevallier J, Cheze B (2008) The EU emissions trading scheme: the effects of industrial production and CO₂ emissions on European carbon prices. *Int Econ* 116:93–125
4. Alberola E, Chevallier J, Cheze B (2009) Emissions compliances and carbon prices under the EU ETS: a country specific analysis of industrial sectors. *J Policy Model* 31:446–462
5. Bai J, Perron P (1997) Estimation of a change point in multiple regression models. *Rev Econ Stat* 79:551–563
6. Bai J, Perron P (1998) Estimating and testing linear models with multiple structural changes. *Econometrica* 66:47–78
7. Bai J, Perron P (2003) Computation and analysis of multiple structural change models. *J Appl Econom* 18:1–22

8. Banerjee A, Dolado JJ, Galbraith JW, Hendry DF (1993) Cointegration, error correction, and the econometric analysis of non-stationary data. Oxford University Press, Oxford
9. Benz E, Trück S (2009) Modeling the price dynamics of CO₂ emission allowances. *Energy Econ* 31:4–15
10. Bollerslev T (1990) Modelling the coherence in the short-run nominal exchange rates: a multivariate generalized ARCH model. *Rev Econ Stat* 72:498–505
11. Bollerslev T, Engle RF, Wooldridge JM (1988) A capital asset pricing model with time-varying covariances. *J Polit Econ* 96:116–131
12. Bunn DW, Fezzi C (2009) Structural interactions of European carbon trading and energy prices. *J Energy Markets* 2:53–69
13. Chevallier J (2011) Anticipating correlations between EUAs and CERs: a dynamic conditional correlation GARCH model. *Econ Bull* 31:255–272
14. Chevallier J (2012) Macroeconomics, finance, commodities: Interactions with carbon markets in a data-rich model. *Econ Model* 28:557–567
15. Chevallier J, Ielpo F, Mercier L (2009) Risk aversion and institutional information disclosure on the European carbon market: a case-study of the 2006 compliance event. *Energy Policy* 37:15–28
16. Christiansen AC, Arvanitakis A, Tangen K, Hasselknippe H (2005) Price determinants in the EU emissions trading scheme. *Climate Pol* 5:15–30
17. Conrad C, Rittler D, Rotfuss W (2011) Modeling and explaining the dynamics of European Union Allowance prices at high-frequency. *Energy Econ*. doi:[10.1016/j.eneco.2011.02.011](https://doi.org/10.1016/j.eneco.2011.02.011)
18. Convery FJ (2009) Reflections—the emerging literature on emissions trading in Europe. *Rev Environ Econ Policy* 3:121–137
19. Convery FJ, Redmond L (2007) Market and price developments in the European Union emissions trading scheme. *Rev Environ Econ Policy* 1:88–111
20. Daskalakis G, Markellos RN (2009) Are electricity risk premia affected by emission allowance prices? Evidence from the EEX, Nord Pool and Powernext. *Energy Policy* 37:2594–2604
21. Daskalakis G, Psychoyios D, Markellos RN (2009) Modelling CO₂ emission allowance prices and derivatives: evidence from the European trading scheme. *J Bank Finance* 33:1230–1241
22. Dalggaard P (2002) Introductory statistics with R. Springer statistics and computing. Springer, New York/Dordrecht/Heidelberg/London
23. Delarue E, D'haeseleer WD (2007) Price determination of ETS allowances through the switching level of coal and gas in the power sector. *Int J Energy Res* 31:1001–1013
24. Dickey DA, Fuller WA (1979) Distribution of the estimators for autoregressive time series with a unit root. *J Am Stat Assoc* 74:427–431
25. Dickey DA, Fuller WA (1981) Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica* 49:1057–1072
26. Ellerman AD, Buchner BK (2007) The European Union emissions trading scheme: origins, allocation, and early results. *Rev Environ Econ Pol* 166–187
27. Ellerman AD, Buchner BK (2008) Over-allocation or abatement? A preliminary analysis of the EU ETS based on the 2005–06 emissions data. *Environ Resour Econ* 41:267–287
28. Ellerman AD, Convery F, De Perthuis C (2010) Pricing carbon: the European Union emissions trading scheme. Cambridge University Press, Cambridge
29. Engle RF (2002) Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *J Bus Econ Stat* 20:39–350
30. Engle RF, Kroner KF (1995) Multivariate simultaneous generalized ARCH. *Econom Theory* 11:122–150
31. Engle RF, Sheppard K (2001) Theoretical and empirical properties of dynamic conditional correlation MGARCH. NBER working paper No 8554, National Bureau of Economic Research, Massachusetts, USA
32. Gujarati DN (2004) Basic econometrics, 4th edn. McGraw-Hill, New York
33. Hamilton JD (1996) Time series analysis, 2nd edn. Princeton University Press, Princeton
34. Harvey AC (1993) Time series models, 2nd edn. Harvester Wheatsheaf, New York
35. Hintermann B (2010) Allowance price drivers in the first phase of the EU ETS. *J Environ Econ Manag* 59:43–56

36. Kanen JLM (2006) Carbon trading and pricing. Environmental Finance Publications, London
37. Keppeler JH, Mansanet-Bataller M (2010) Causalities between CO₂, electricity, and other energy variables during phase I and phase II of the EU ETS. *Energy Policy* 38:3329–3341
38. Kleiber C, Zeileis A (2008) Applied econometrics with R. Springer series use R! Springer, New York/Dordrecht/Heidelberg/London
39. Kwiatkowski DP, Phillips PCB, Schmidt P, Shin Y (1992) Testing the null hypothesis of stationarity against the alternative of the unit root: how sure are we that economic time series are non stationary? *J Econom* 54:159–178
40. MacKinnon JG (1996) Numerical distribution functions for unit root and cointegration tests. *J Appl Econom* 11:601–618
41. Mansanet-Bataller M, Pardo A (2009) Impacts of regulatory announcements on CO₂ prices. *J Energy Mark* 2:77–109
42. Mansanet-Bataller M, Pardo A, Valor E (2007) CO₂ prices, energy and weather. *Energy J* 28:73–92
43. Paolella MS, Taschini L (2008) An econometric analysis of emission allowance prices. *J Bank Finance* 32:2022–2032
44. Phillips PCB, Peron P (1988) Testing for a unit root in time series regression. *Biometrika* 75:335–346
45. Roll R (1984) Orange juice and weather. *Am Econ Rev* 74:861–880
46. Shumway RH, Stoffer DS (2011) Time series analysis and its applications with R examples, 3rd edn. Springer texts in statistics. Springer, New York/Dordrecht/Heidelberg/London
47. Zeileis A, Kleiber C (2005) Validating multiple structural change models—a case study. *J Appl Econom* 20:685–690

Econometric Analysis of Carbon Markets
The European Union Emissions Trading Scheme and
the Clean Development Mechanism

Chevallier, J.

2012, XXX, 217 p., Hardcover

ISBN: 978-94-007-2411-2