INTERACTION OF EUROPEAN CARBON TRADING AND
ENERGY PRICES*

Derek W. Bunn† and Carlo Fezzi‡

March, 2007

ABSTRACT

This paper addresses the economic impact of the EU Emission Trading Scheme for carbon on wholesale electricity and gas prices. Specifically, we analyse the mutual relationships between electricity, gas and carbon prices in the daily spot markets in the United Kingdom. Using a structural co-integrated VAR model, we show how the prices of carbon and gas jointly influence the equilibrium price of electricity. Furthermore, we derive the dynamic pass-through of carbon into electricity price and the response of electricity and carbon prices to shocks in the gas price.

*We would like to thank Sirio Aramonte, Luca Fanelli, Stefano Sacchetto and an anonymous referee for their helpful comments. A preliminary version of this paper was presented at the EAERE Summer School held in Venice, from June 25th to July 1st, 2006, and supported by the Marie Curie series of conferences "European Summer School in Resource and Environmental Economics".

†Corresponding Author Address: Department of Decision Science, London Business School, Sussex Place, Regent’s Park, NW1 4SA, London (UK); e-mail: dbunn@london.edu.

‡Address: CSERGE, School of Environmental Sciences, University of East Anglia, Norwich, NR4 7TJ (UK); e-mail: c.fezzi@uea.ac.uk
1 Introduction

As part of its commitment to the Kyoto Protocol, in January 2005 the European Union implemented a scheme of tradable CO$_2$ emission permits, whereby restricted allowances were allocated to various industrial emitters of carbon dioxide, specifying the amount of CO$_2$ they can emit each year. At the end of each year, companies must produce permits to cover their tonnes of CO$_2$ emitted. Since companies are allowed to trade permits freely with one another within the EU, the scheme was intended to ensure not only that overall emissions would be reduced, but also that the cuts are made by those firms that can achieve the most efficient abatement costs (European Commission, 2003). With the success of this scheme having major implications, not only for the continuing commitment of the EU to greenhouse gas abatements, but also to other countries and regions which are considering the introduction of a similar scheme, its progress has been subject to intense scrutiny, even before substantial empirical evidence has accumulated (European Commission, 2005; Smale et al. 2006, Sijm et al. 2006, Bentz and Trück 2006).

Prior to the emergence of actual evidence from carbon trading in practice, extensive theoretical and simulation analyses have speculated upon its broad effects (eg, McKibbin et al. 1999, Criqui and Viguier 2000, Böhringer 2002, Böhringer and Lange 2005, Barreto and Kypreos 2004, Huntington and Weyant, 2004). Regarding the EU power sector in particular, Linares et al. (2006) comment upon the Spanish situation, and Hauch (2003) on the Nordic region. Despite the longer term policy insights that such studies provided, the first phase of the EU Emission Trading Scheme (ETS) was introduced as an experiment, with open questions upon the short term properties of the carbon prices. The initial behaviour of the prices has indeed raised several concerns. In the first few months of 2005, carbon allowances were traded at about €7/tonne, raising steadily to a peak over €29/tonne in July, before falling back to around €20/tonne a month later and fluctuating around that level during the rest of 2005. As daily trading essentially reflects a forward market on the annual commitment to settle emissions with permits, such volatility not only reflects basic uncertainty in the underlying annual price of abatement, but substantially adds to the risk management costs of participants. By April 2006, daily prices had again risen over €30/tonne, falling precipitously during three days at the end of the month to below €10/tonne when the first
settlement news appeared and it became apparent that far less abatement had been needed in the first year than
the market had been expecting. Shocks of that magnitude affect the asset values of power companies with, for
example, British Energy losing 5% of its stock market value during those three days in April 2006. By January,
2007, spot carbon prices had fallen to €4/tonne, but forward prices for 2008 were trading around €16/tonne. The
result of such uncertainty created investment aversion in the industry, to the extent that the major companies
were identifying carbon price risk as the major factor in investment delays, despite institutional concerns about
security of supply (Blyth, 2007).

Hence the objective of this paper is to analyse, econometrically, evidence from the first two years of the
EU ETS, with the aim of determining its interrelationship with gas and power prices. Specifically, we propose a
structural, cointegrated vector autoregressive (SVAR) model, estimated on daily market data, which encompasses
both short-run and equilibrium relations between electricity, gas and carbon prices. From this, we can estimate
the transmission of shocks between gas, carbon and power prices, and thereby address questions on the short term
economic impact and potential efficiency of the scheme. The paper is organised as follows: section 2 presents the
main features of the interaction between carbon, gas and electricity prices, section 3 introduces the statistical
framework regarding the structural cointegrated VAR model, and section 4 describes its estimates on the EU
ETS data. Section 5 concludes.

2 Carbon price formation and the electricity market

As for any other freely-traded product, the price of carbon allowances is determined by the balance between
supply and demand. In the case of carbon permits, it is appropriate to distinguish between the short term daily
market, where trading actually happens, and the ‘long term’ settlement (each multiyear Phase of the scheme),
where the mandatory requirements of the scheme are balanced and audited. Initially the EU ETS was designed
to operate through two Phases (Phase 1: 2005-2007; Phase 2: 2008-2012). Each member state of the EU agrees
on a national allocation plan (NAP) for annual abatement for each Phase, based upon a restricted percentage
of the “business as usual” projection of emissions from particular facilities. Thus there is an annual requirement
for abatement (in tonnes CO$_2$), $D_j$, ($j = 1, 2$ for Phases), which will be uncertain because of the underlying “business as usual” baseline. Across the EU there exists essentially a supply function for abatement, $f(.)$, reflecting the increasing marginal costs within a year of reducing a tonne of CO$_2$. Thus, in terms of the power sector responsiveness in the short run, for low levels of abatement $f(.)$ will reflect the substitution of German lignite by hard coal, then the more expensive option of replacing hard coal by gas (mainly in Spain and the UK) will appear further up this abatement supply function. Thus, the supply function is convex, discontinuous, uncertain and variable throughout the year, reflecting the switching costs between primary fuels. Essentially, therefore, agents trade in the daily market, buying and selling carbon allowances, against their own expectations, $E_t[f(D_j)]$, which evolve through the year on the annual equilibrium price for carbon.

Furthermore, to the extent that annual allowances are granted to the scheme participants at the beginning of each Phase, and that a daily price for carbon emerges from the markets, these allowances reflect new liquid assets (some critics argue that polluters have been given windfall profits in the short term), and thus their consumption (eg. to produce power) involves the opportunity cost of carbon at the market price (see also Sijm et al. 2006). Of course, production in excess of allowances does require the direct purchase from the market of an allowance. So it is to be expected that the price of carbon will be an additional increment to the short-term fuel costs of power
generation, the aggregate effect of which will depend on the technology mix across the whole of the EU and the pricing behavior of firms.

Figure 1 shows the sample of data used in this study, weekdays from April 2005\(^1\) to May 2006, with UK electricity and gas prices (upper plot), as well as EU carbon allowances (lower plot). Whilst gas and power prices are closely related, carbon seems quite distinct. Evidently, fundamental analysis would suggest that gas shocks should transmit to power, and power shocks could transmit to gas if the power market is a substantial part of the gas market, which is the case in the UK but not in EU as a whole. Moreover, both electricity and gas consumption are influenced by weather conditions. As for carbon price, the structural considerations illustrated above (i.e. the coal to gas switching) might suggest that in a closed system it would be substantially dependent upon gas prices, but this would be confounded in a particular case with national markets for gas and power, given the much wider EU market for carbon.

Despite, therefore, these structural considerations, because of the intricate and confounding nature of the interrelationships, we approached the model specification through the data-driven paradigm, as advocated in Sims (1980), Hendry and Mizon (1993). In other words, firstly data dynamics are modelled through a detailed statistical specification without imposing any 'a-priori' economic restriction and, only in a second step, the structural model is derived with a downward testing procedure as a restriction of the statistical model describing the data.

The three series did not reject unit root tests on levels, whilst differences appeared to be stationary\(^2\). Therefore, in order to avoid the risk of spurious regression, we modeled the series as I(1) with a cointegration methodology (following Johansen, 1991). This technique seeks to ensure valid inference in non-stationary systems. So far, it has been used predominantly to estimate long-run macroeconomic relationships. Implementations in high-frequency context are less common: Baillie and Bollerslev (1989) and Diebold et al. (1994) have used it to evaluate

\(^1\)From April 2005, the England and Wales power market expanded to include Scotland.

daily financial market outcomes, whilst in the electricity market context, Fezzi and Bunn (2006) estimated two cointegrating vectors for daily supply and demand interactions.

3 The model

We implement a structural cointegrated VAR model, following Pesaran and Shin (1998), Garratt et al. (1998). This methodology merges the structural VAR approach with the cointegration technique, having the attractive feature that the estimated equilibrium relationships give a clear economic interpretation whilst the short-run dynamics are flexibly estimated in a VAR specification. Structural VARs were introduced by Bernanke (1986), Sims (1986) and Blanchard and Quah (1989), in response to criticism regarding the “lack of economic interpretability” (Cooley and ReLoy, 1985) of the classical VAR approach proposed in Sims (1980). In a classical VAR all the variables are modelled as endogenous a priori, as a function of their on past values, i.e. as:

\[ y_t = A_1 y_{t-1} + A_2 y_{t-2} + \ldots + A_p y_{t-p} + u_t, \quad (1) \]

with \( y_t \) = vector of \( n \) endogenous variables, \( A_1, \ldots, A_p = n \times n \) regression matrices, \( p \) = number of lags chose to ensure no serial correlation in the residual component \( u_t \) with covariance matrix \( \Sigma_u \). Equation (1) is a reduced form since the contemporaneous relations between the endogenous variables are not modelled and therefore it may difficult to give to the residual a direct economic interpretation, especially if the cross-correlation matrix \( \Sigma_u \) contains high values. Alternatively, the structural VAR has been developed to transform the reduced form VAR model into a system of structural equations, whose impulse response function and variance decomposition present, in principle, direct economic meanings. This can be achieved either by imposing restrictions on the residual cross-correlation matrix or on the long-run relations. A SVAR model can be written in the form:

\[ B_0 y_t = B_1 y_{t-1} + B_2 y_{t-2} + \ldots + B_p y_{t-p} + \varepsilon_t, \quad (2) \]

where \( \varepsilon_t = B_0 u_t \), \( B_q = B_0 \ast A_q \), \( q = 1, \ldots, p \) and the correlation matrix of the residuals is \( \Omega = B_0 \Sigma_u B_0 \) (in general equal to the identity matrix). Considering only short-run restrictions (for long-run restrictions see
Blanchard and Quah, 1989) one has to impose \( n \times (n - 1)/2 \) restrictions on the matrix \( B_0 \) (plus the normalisation restrictions achieved by setting the covariance matrix of the structural shocks to identity) in order to identify all the parameters of equation (2) from the reduced form model (1). These restrictions should, in general, be motivated by economic theory (see, among others, Amisano and Giannini, 1997). In this paper, we derive them from two auxiliary regressions, in the next section.

The SVAR technique has also been implemented in vector error-correction models with cointegrated variables. The Johansen (1991) procedure for testing the presence of cointegrating vectors starts with a reduced form VAR model (equation 1), and therefore without imposing any ‘a priori’ restrictions. The model can be re-written in the following error-correction form:

\[
\Delta y_t = \Pi y_{t-1} + \Gamma_1 \Delta y_{t-1} + ... + \Gamma_{p-1} \Delta y_{t-p+1} + u_t ,
\]

where \( \Pi = A_1 + A_2 + ... + A_p \) and \( \Gamma_i = -(A_{i+1} + ... + A_p) \). Model (3) can be augmented considering the simultaneous interactions between endogenous variables and therefore giving structural meaning to the residual component:

\[
B_0 \Delta y_t = \Psi y_{t-1} + \Lambda_1 \Delta y_{t-1} + ... + \Lambda_{p-1} \Delta y_{t-p+1} + \varepsilon_t ,
\]

where equation (3) can be obtained simply pre-multiplying the system by \( B_0^{-1} \). Thus, to compute the responses to the economic shocks \( \varepsilon_t \), one has to link the forecast errors \( u_t \) in the reduced form model (3) to the structural residuals \( \varepsilon_t \) through the identity: \( \varepsilon_t = B_0 u_t \). In the next section we show how to identify the residual matrix, based on two auxiliary regressions.

Our modelling approach starts from a reduced form VAR considering electricity, gas and carbon prices as potentially endogenous ‘a priori’. Furthermore, we include, as exogenous variables, atmospheric temperature (which is the most important determinant of electricity and gas demand on daily basis) and three dummy variables in order to capture the huge drop in carbon price over three days, following news of the settlement, at the end
of April 2006. In this model the main purpose of the exogenous variables is to capture the co-movements of the endogenous ones and, therefore, highlight the interactions among the endogenous. As shown, for instance, by Engle et al. (1986), the energy demand (and, therefore, price) and temperature relationship is a highly non-linear ‘V’ shaped function, since energy is used for both heating and cooling purposes. Thus, following an explorative analysis, we identify a threshold at which the price-temperature gradient reverses and define two variables and a dummy from the original temperature, namely cold temperature, \( t_{\text{cold}} \), hot temperature, \( t_{\text{hot}} \) and \( d_{\text{temp}} \).

Defining \( y_t' = [p_{\text{electricity}}, p_{\text{gas}}, p_{\text{carbon}}] \), \( z_t' = [t_{\text{hot}, t}, t_{\text{cold}, t}, d_{\text{temp}}] \)\(^3\) and \( x_t' = [y_t', z_t'] \), and \( d_t \) = deterministic term containing centered seasonal dummies to capture the weekly seasonality and three dummy variables encompassing the carbon shock, the reduced form VECM system can be written as:

\[
\Delta y_t = \omega \Delta z_t + \alpha \beta y_{t-1} + \Gamma_1 \Delta y_{t-1} + \ldots + \Gamma_{p-1} \Delta y_{t-p+1} + C d_t + u_t .
\] (5)

In this model temperature and deterministic factors affect the short run dynamics of the price series that revert towards the equilibrium vector(s) \( \beta y_{t-1} \) according to the adjustment coefficients \( \alpha \). Thus, it is possible to identify the structural interactions among the variables by imposing restrictions on the matrix \( B_0 \) (eq. 4), which we do in the next section through two auxiliary regressions.

4 The results

The above model is estimated using day-ahead electricity (UKPX) and gas prices (NBP) for United Kingdom and European carbon emission price (source: Platts). Atmospheric temperature is represented by the daily

\(^3\)The model is actually estimated using the differenced variables \( \Delta t_{\text{cold}} \) and \( \Delta t_{\text{hot}} \), which are not simply the first differences of \( t_{\text{cold}} \) and \( t_{\text{hot}} \). In fact, to linearise a "V" relation in the first differences, one has to consider that if during the intra-period variation the temperature crosses the threshold the relationship is reverted. To overcome this problem \( \Delta t_{\text{hot}} \) is defined as all the variation of the temperature that occurs above the threshold and as \( \Delta t_{\text{cold}} \) all the variation that occurs below. If, for instance, the threshold is 60°F and temperature drops from 63°F to 55°F, \( \Delta t_{\text{hot}} = -3 \) and \( \Delta t_{\text{cold}} = -5 \). Furthermore, on the first differences, the dummy disappears.
average temperature in London, available from the archive provided by the University of Dayton. We transform the endogenous variables (electricity, gas and carbon prices) into their natural logarithms to reduce variability, and thus obtaining directly the elasticity values from the parameter estimates. We estimate model (5) with one lag in the endogenous variables (selected by the Hannan-Quinn criterion), and test for the number of cointegrating vectors using the trace test introduced in Johansen (1991). We restrict the intercept to lie in the cointegration space since we do not find evidence of a trend in the dynamics of the variables.

The results, reported in table 1, strongly support the presence of one cointegrating vector. Observing the cointegrating coefficients, we are reassured that all the estimates have plausible signs. Furthermore, they are all significant according to the Likelihood Ratio (LR) test as showed in Johansen (1996). The coefficients can be interpreted as price elasticities, implying, for instance, that a gas price rise of 1%, would, in equilibrium, be associated with an electricity price rise of 0.63%. Furthermore, since all the coefficients are strongly significant, all the price variables are important to define the equilibrium vector, i.e. both carbon and gas prices are crucial to define the level to which electricity price is attracted over time.

Even though useful to understand the equilibrium price of electricity in the “long run”, this cointegrating

---

\[ \text{Table 1: Cointegration tests and vector estimates with LR test} \]

\begin{tabular}{|c|c|c|c|c|}
\hline
Trace Test & \\
\hline
\text{Ho} & \text{r} & \text{n-r} & \text{p-value} & \text{eigenv.} \\
\hline
0 & 2 & 54.090 & 0.000 & 0.1223 \\
1 & 1 & 11.821 & 0.474 & 0.0253 \\
2 & 0 & 3.5225 & 0.499 & 0.0108 \\
\hline
\end{tabular}

\begin{tabular}{|c|c|c|c|}
\hline
\text{Cointegrating vector estimates} & & & \\
\hline
1_\text{electricity} - 0.628p_{\text{gas}} - 0.428p_{\text{carbon}} - 0.592 & & & \\
[...], [-11.926], [-3.985], [-1.842] & & & \\
\hline
\end{tabular}

---

\footnote{Since exogenous and deterministic variables are included, and thus the original critical values are no longer valid, we compute the approximated \( p \)-values based on Doornik (1998).}
Table 2: Vector error-correction model estimates and tests, t-ratios in parenthesis

vector does not contain any information regarding the short term interactions of those prices (matrixes $B_0$ and $\Lambda_i$, $i = 1, ..., p$, in model 4) nor how fast each of the variables moves towards the equilibrium (matrix $\alpha$ in model 5). In order to analyse these issues we estimate model (5) with the software jmulti (Lütkepohl and Krätzig, 2004) using 3SLS and eliminate the non-significant coefficients through a recursive procedure, i.e. sequentially excluding the regressors with the lowest t-ratio and ultimately minimising the HQ criterion (see Brüggemann and Lütkepohl, 2001).
Table 3: Auxiliary regressions estimates

The final estimates are reported in table 2. According to the adjustment coefficient values (see Johansen, 1991) there is evidence of long-run weak exogeneity in the carbon price. Nevertheless, carbon price is influenced by lagged gas price, even though the significance level is not very high. Although there is no serial correlation, there is evidence of ARCH and non-normality in the residuals. However, this is not likely to be a major problem in our cointegration analysis since the Johansen ML estimator present small sample properties consistent with the asymptotic values even this drawbacks are present (see Gonzalo, 1994). Observing the correlation matrix we see how the cross-correlation between gas and electricity residuals is quite high and, on the other hand, how the cross correlation between carbon residuals and the others is fairly low. In order to identify matrix $B_0$ (model 4) and give structural meaning the residuals we need to impose 3 restrictions on the $B_0$ matrix itself.

---

Normality test computed as in Doornik and Hansen (1994); AR LM test computed regressing the residuals on the explanatory variables and lagged residuals; Arch LM test computed regressing the squared residuals on the lagged squared residuals, as in Lütkepohl H., Krätzing M. (2004).
Because of the low magnitude of the cross correlation involving carbon residuals, two of the restrictions can be imposed on them without substantially changing the results. Most important is the restriction regarding the interaction of electricity and gas price, given the high-value of the cross-correlation, and it is clearly crucial to understand if this high cross-correlation is caused mainly by gas price influencing electricity price or vice versa. To investigate this we conduct two auxiliary $ADL(1,1)$ regressions using instrumental variables. The first equation measures the instantaneous effect of the gas price on the electricity price, using as instruments the gas available in the storage facilities (source: National Grid) and the quantity of gas flowing through the Zeebrugge-Bacton interconnector, the only gas interconnection between UK and Europe at the time. Using $w_t = [t_{hot,t}, t_{cold,t}, d_{temp,t}, p_{gas,t-1}, p_{electricity,t-1}, t_{hot,t-1}, t_{cold,t-1}, d_{temp,t-1}]$ we can write:

$$p_{electricity,t} = b_0 + b_1 p_{gas,t} + \theta' w_t + \epsilon_{et}.$$

The second equation\(^6\) measures the effect of electricity on gas prices, and uses as instruments the excess generation capacity available on the system (source: National Grid) and can be written as:

$$p_{gas,t} = \delta_0 + \delta_1 p_{electricity,t} + \vartheta' w_t + \epsilon_{gt}.$$

The estimates of both regressions with 2SLS are reported in table 3\(^7\). Since the parameter $b_1$ do not appear to be significantly different from zero, whereas $\delta_1$ is strongly significant, we can conclude that the high-cross correlation between gas and electricity residuals is due to the influence of gas on electricity, and not the other way round. Therefore, we impose the restriction on the matrix $B_0$ and obtain the equations relating the structural residuals $\epsilon_t$ to the reduced form residuals $u_t$:

$$u_{elect,t} = \epsilon_{elect,t} - b_{12} \epsilon_{gas,t} - b_{13} \epsilon_{carb,t},$$

$$u_{gas,t} = \epsilon_{gas,t} - b_{23} \epsilon_{carb,t},$$

$$u_{carb,t} = \epsilon_{carb,t}.$$

\(^6\)In the gas price regression actual temperature is used, since the V relation holds for electricity only.

\(^7\)Heteroskedasticity robust standard errors following White (1980).
with matrix $B_0$ equal to:

$$
\begin{bmatrix}
1 & * & * \\
0 & 1 & * \\
0 & 0 & 1
\end{bmatrix}.
$$

Given these restrictions, we use the Maximum Likelihood procedure (Amisano and Giannini, 1997) to estimate matrix $B_0$ in model (4) and we use it to derive the dynamic response of the system to a shock on one of the structural residuals. This approach is useful to determine the dynamic impact, for instance, of a carbon price shock (e.g. at the end of April 2006) on electricity and gas price. As showed, for instance, in Lütkepohl and Krätzig (2004), this can be achieved by simply re-arranging equation (5) as a function of the residuals, and directly obtaining the dynamic impact of a shock at any lag. We use bootstrapped confidence intervals, as in Hall (1992), with 500 bootstrap replications. The estimated dynamic impact on the three prices of a sudden increase in carbon prices is reported in figure 2.

As shown, a carbon price shock produces a significant increase in the electricity price. Furthermore, even though the instantaneous reaction of electricity prices is significant, carbon price is fully passed-through only after some days. Gas price also increases but, at least in the first days, the increment is not significant. In the long run the price of gas is higher than before the shock, in line with the electricity price. A shock on gas prices as a similar effect: in line with the theory, it increases the overall prices of the three commodities. Nevertheless, the temporal dynamics and the magnitudes are different. In fact a gas price increase has its highest impact over the first few days and then its effect fades.

5 Conclusions

Using a structural, cointegrated VAR model, we show how carbon price is important in formulating the equilibrium price of electricity and gas in the UK, and that it is essentially exogenous. We also identify the
Figure 2: Impulse response functions for electricity, gas and carbon; shock on carbon price. Dotted line = 95% bootstrapped confidence intervals.

Figure 3: Impulse response functions for electricity, gas and carbon; shock on gas price. Dotted line = 95% bootstrapped confidence intervals.
short-term dynamics and show that carbon prices react significantly and quickly to a shock on gas price, but, in turn, the dynamic pass-through of carbon to electricity price is only after some days. In particular, we estimated that eventually a 1% shock in carbon translates on average into a 0.42% shock in UK electricity, with [0.21; 0.64] as a 95% confidence interval. Essentially we see that gas drives carbon, whilst both carbon and gas drive electricity prices. Evidently one of the indirect effects of carbon trading has been to strengthen the link between gas and power, and to the extent that global gas prices are acquiring the geopolitical risk characteristics of oil, that may not be a welcome outcome.

6 REFERENCES


