ECONOMETRIC ANALYSIS OF THE INTERACTION BETWEEN THE EUROPEAN EMISSION TRADING SCHEME AND ENERGY PRICES

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PRELIMINARY AND INCOMPLETE[1]

Abstract

This paper addresses the economic impact of the European Emission Trading Scheme Directive on wholesale electricity and gas prices in Europe. Specifically, I analyse the relationships between electricity, gas and carbon prices in two countries with a distinct power generation structure: Germany and United Kingdom. I propose two complementary econometric models in order to empirically estimate the interactions between the variables in the system. The first one is a VAR model, and it is specially designed for analyzing the dynamics of the variables if subjected to unexpected shocks. The second one is a simultaneous equation, vector error correction model (VECM), used to identify the economical structural relationships that relate the variables, distinguish between short and long run. Both models are empirically estimated on day-ahead (spot) and month-ahead (forward) market data, covering the first year of time span after the launch of the ETS on the 1st of January 2005.

Keywords: Carbon Emission Trading, Energy Markets, Structural Vector Autoregression

[1] This paper has been written during a period as visiting research student at the Department of Decision Science, London Business School. I am especially indebt to Derek Bunn, Michele Costa and Attilio Gardini for their suggestions and overall guidance. The support of the University of Bologna under the Marco Polo fellowship is gratefully acknowledged.

1 Introduction

In 1997, adopting the Kyoto Protocol, almost 200 countries participated to the first initiative of the international community to moderate the global warming (UNFCC, 1998). The most important feature of the Protocol is the quantified emissions limitations and reduction commitments of greenhouse gases (among which, the most prominent is CO_2) ratified by the compliant countries. Countries have agreed upon a system of unequal percentage reduction or limitations, which would result, in 2012, in an overall cut of 5% of greenhouse gases compared to 1990 levels.

The most significant initiative of the European Union to fulfil the Kyoto target is the Emission Trading Scheme (ETS), regulated by the directive 2003/87/EC of the European Commission (2003). According to the ETS, tradable allowances are allocated to industrial emitters of carbon dioxide (CO_2), specifying the amount of CO_2 they can emit each year. Since companies are allowed to trade permits freely with one another within the EU, the scheme should ensure not only that overall emissions are reduced, but also that the cuts are made by those firms that provide lower abatement costs. Hence the economic impact of reducing emission CO_2 should be minimised.

The effects of carbon emission trading on the energy sector have been subject to extensive research in the last years. The leading approach has been to develop large economic models and evaluate through simulation techniques the economic effects of emission trading within different scenarios (a detailed review can be found in Huntington and Weyant, 2004). Some of the contributions cover a broad range of effects on large regions and many sectors (see, for instance McKibbin et al. 1999, Criqui and Viguer 2000, Böhringer 2002, Barreto and Kypreos 2004). Others have focused on the impact on specific countries and sectors. Among them, I may cite the work of Linares et al. (2006) on the Spanish electricity sector, and the one of Hauch (2003) on the Nordic countries energy sector. Since the bulk of these studies have been undertaken before the ETS itself, their contribution was mainly focus on deriving policy recommendations, in particular comparing the impact of distinct resolutions in diverse scenarios. Determine the price that the market will assign to carbon emission allowance was a key issue since, prior to 2005, there was no data available on this quantity[2].

The approach undertaken in this paper is rather different since it strongly relies on empirical data collected in the first year since the ETS was launched. I propose two distinct but complementary econometric models, in order to uncover and empirically estimate different aspects of the composite interrelationships between electricity, gas and carbon emission allowances prices.

The first one is a model specified to analyse simultaneously the temporal dynamic of these variables, and identify the casual relationships and the main drivers of the system. These insights

[2] Future products for carbon allowances were traded since the beginning of 2003. This market has been characterised by a very low liquidity, reflecting the scarcity of information of the agents regarding the future value of carbon. Therefore these prices cannot be considered as reliable indicator of the true value of carbon credits.

are uncovered implementing the VAR methodology, developed by Bernanke (1986), Sims (1986) and Blanchard and Quah (1989), and introduced by the original work of Sims (1980). When the residual of the equations are uncorrelated with each others, the reduced form VAR is equivalent to a structural VAR, and the error-terms assume structural economic meaning. In this paper the model is explicitly design to estimate the reaction of the system of prices if subjected to different types of shocks. For instance, it is used to empirically estimate the pass-through of a variation of carbon price into electricity and gas prices. As showed in section 3, the reactions of electricity prices to a shock on gas prices and to a shock on carbon prices are fundamentally different.

The second model is a simultaneous equation, vector-error correction model, based on a simple economic model consisting in a system of structural equations describing the interactions of electricity, gas and carbon prices. As illustrated in section 2.2, the variables of the system appear to not to be stationary. For this reason, the estimation technique cannot be based on the classical statistical inference tools (for an illustration see, Hendry and Juselius, 2000). The cointegration methodology developed by Johansen (1988, 1991) seems to constitute an appealing possibility. As illustrated in Davidson (1998), the identified cointegrating relations represent structural economic relationships with direct economic meaning. In this framework these equations are identified with the supply and demand function for electricity, the supply and demand function for gas, and the function of supply for carbon emission permits. This part is still work in progress; the main issues and possible insights are illustrated in section 4.

The paper is organised as follows: section 2 and 3 are dedicated to the first modelling approach; section 2.1 presents the main features of the interaction between carbon, gas and electricity prices whereas section 2.2 introduces the statistical framework regarding the VAR model. In section 3 are illustrated the empirical specification and the results. Section 4 concludes presenting the main characteristics of second modelling approach and the core objectives of the ongoing research.

2 The mutual interactions between electricity, gas and carbon emission prices

2.1 The dynamics of carbon prices and the interactions with fuel and electricity prices

Phase 1 of the European Emission Trading Scheme was launched on the first of January 2005. In the first few months, carbon allowances were traded at about 7€ a tonne. They rose to a peak over 29€ a tonne in July, before falling back to around 20€ a month later and fluctuating around that level during the rest of 2005. Fluctuations of this scale are a clear indication about the uncertainty of the market regarding the 'true' value of carbon emission permits.

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 short term (the daily market) and 'long term'. In the first year of the ETS the latter can be identified with the 30th of April 2006, when operators will be required to surrender sufficient allowances. In the 'long term', the demand function is vertical, since the available stock of allowance throughout the EU is essentially fixed[3] and determined by the government of each member state in a National Allocation Plan (NAP). For this reason, the 'long term' equilibrium price of carbon emission permits is determined exclusively by the supply curve, which is influenced by the marginal cost of abatement curve. This curve takes into account all the economic costs faced by the firms in order to cut CO_2 emission. For power generating companies it includes installing new technologies, switching to less carbon intensive fuels (for example, from coal to gas), or simply cutting the production of electricity[4].

For this reason it is clear how the position of the abatement cost curve is affected, inter alia, by the price of electricity and by the price of fossil fuels, namely coal and gas, and in particular by their relative price (a coal-fired power station emits a quantity of carbon per MWh that is approximately two times the quantity emitted by a gas-fired one). After the liberalization of the power sector, both gas and electricity became commodities traded on a daily (or hourly) basis, and their prices have been characterized by extremely high volatility. In particular for electricity it is not uncommon to observe a variation of 200% in the price level on weekly basis. It is still uncertain how these extreme fluctuations are reflecting in carbon prices.

As one would expect, the direction of causation is two-sided. Since January 2005, most of the power generators started to include carbon price in offering their bids to the wholesale electricity markets (see European Commission, 2005). The extent of the pass-through of carbon prices into the electricity prices is still an open question, since it reflects the power generation fuel-mix of each country and in particular the fuel burned by the marginal plants (i.e. the ones which set the prices in auction markets). Furthermore, if one considers that coal is a world-wide traded commodity, whose dynamics are independent from the ones of carbon emission permits in Europe, (the main consumers of coal are China and US) the dynamics of gas price are likely to be related to those of carbon emission permits to the extent that gas prices may depend substantially upon power consumption in some countries (for example U.K., where the gas-fired power plants generate around the 40% of electricity).

These complex interactions are analysed in this paper using a VAR model. As shown in section 2.2, the model is specifically designed to empirically estimate the dynamic reactions of the

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[3] In practice it is possible to create allowances by undertaking certain types of environmentally friendly investment in developing countries. However, in comparison with the total stock of allowances issued by all 25 member states, this is unlikely to be substantial.

[4] In the daily market the situation is slightly different, since demand function is no longer fixed but determined by the offers made by companies that are willing to sell emission permits. In this market the clearing price is influenced, inter alia, by the differences in the abatement costs among the participating firms and by the agent's expectations regarding the future price of carbon allowances.

system of prices when subject to specific shocks. The empirical estimate of the pass-trough of a carbon prices shock to electricity and gas prices is presented, inter alia, in section 3.

2.2 *The statistical framework*

As argued by Sims (1980) in his influential paper, VARs held out the promise of providing a coherent and credible approach to data description, forecasting, structural inference and policy analysis. VARs are now probably the most popular technique for the analysis of the dynamic of macroeconomic time series.

In the classical, reduced form VAR, all the variables are considered as endogenous, and modelled as a linear function of their own lagged values and the lagged values of the other variables of the system. When it is possible to identify variables that influence the endogenous but are not directly affected by them, the model can be augmented by adding current and lagged values of those variables. In this framework the vector of endogenous consist of electricity, gas and carbon price, while the vector of predetermined variables contains oil price, coal price and atmospheric temperature, as a proxy for electricity and gas demand. In this context, the main purpose of these variables is to isolate the effects among the endogenous ones. The relationship among temperature and demand (and hence, price) is non-linear and 'U' shaped (for an illustration see Engle et al., 1986). A possible way to linearise this relation is to define two thresholds. When temperature is lower than the first one, electricity and gas are used mainly for heating purposes and the relation has a negative slope; between the two thresholds the consume of electricity and gas is at its lowest level and almost constant; above the second threshold electricity is used for air conditioning, hence the relation with temperature is positive, whilst gas demand remains at its previous level.

Indicating with $Y_t = [p_{el}, p_{gas}, p_{carb}]$ the vector of endogenous containing the price of electricity, gas and carbon emission permits and with $X_t = [t_{cold}, D_{cold}, t_{hot}, D_{hot}, p_{oil}, p_{coal}]$ the vector of predetermined variables (with t_{cold} the temperature below the first threshold and with D_{cold} its dummy variable, t_{hot} the temperature above the second threshold and with D_{hot} its dummy, p_{oil} and p_{coal} oil and coal prices) the model can be written as:

$$Y_t = \phi(L)Y_t + \varphi(L)X_t + \mu + \varepsilon_t \qquad (1)$$

Where ε_t a the residual term, serially uncorrelated and distributed as $N(0,\Sigma)$, $\phi(L) = \phi_1 L^1 + \phi_2 L^2 + ... + \phi_p L^p$ and $\varphi(L) = \varphi_0 + \varphi_1 L^1 + ... + \varphi_\kappa L^k$ are polynomials in the lag operator L, μ is the vector of the means, k and p number of lags long enough to ensure absence of autocorrelation. Since the regressors are the same in each equation, the model can be estimated with OLS.

The model (1) can be re-written in its moving average representation in order to model the variation of the endogenous not attributed to the predetermined variables as a function of the current and lagged innovations (i.e. current and lagged residuals):

$$Y_t - \frac{\varphi(L)}{1-\phi(L)} X_t - \frac{\varphi(L)}{1-\phi(L)} \mu = \frac{1}{1-\phi(L)} \varepsilon_t$$

Where:

$$[1-\phi(L)]^{-1} = \varepsilon_t + \eta_1\varepsilon_{t-1} + \eta_1\varepsilon_{t-2} + \dots$$

The row i, column j element of the matrix η_r identifies the consequences of a one-unit increase in the j-th variable's innovation at date *t* - *r* for the value of the i-th variable at time *t*. Plotting this value as a function of *r* generates an impulse-response function that describes the response of $y_{j,t+s}$ to a one-time impulse in $y_{i,t}$ with all the other variables held fixed (for an extensive illustration of these concepts see, for instance, Hamilton 1994). For instance, in model (1) it can be used to derive the dynamic reaction of electricity prices to a shock on carbon prices. This is effectively the dynamic pass-through of carbon price into electricity prices.

3 Empirical model specification and results

3.1 *Preliminary data analysis*

The model presented in sections 3 is empirically estimated on day-ahead market data for United Kingdom (NBP gas prices, UKPX electricity prices) and Germany (TTF[5] gas prices, EEX electricity prices). Coal prices are represented by the steam coal ARA price index, oil prices by the London crude oil Brent index, and atmospheric temperature by the daily average temperature in London and in Munich, available from the archive provided by the University of Dayton. The time period covered by the analysis runs from the 1st of January 2005 to the 14th of December 2005. I discard the weekends, since electricity and gas prices present a strong weekly seasonality, related to the dynamics of demand and to the working habits of the population, which would create substantial disturbance in the analysis without providing more insights (for an extensive illustration of this feature see, for instance, Bunn 2000, and Knittel and Roberts 2006). This leaves a total amount of 207 daily observations.

[5] Title Transfer Facility (TTF) is actually a Netherlands market, but the price of gas traded in this market corresponds almost perfectly to one of gas traded in the less liquid Bunde Hub German market.

The price series (in their natural logarithms) and the temperature in Munich (the temperature in London follows a similar path) are plotted in figure 1. The strong link between electricity and gas price seems evident from the plot, while carbon and coal prices seem to follow opposite paths. This dynamic is consistent with the intuition that, since a coal-fired power station is more carbon-intensive then a gas-fired one, when the relative price of coal is decreasing the demand of carbon permits will increase and so, its price.

All the series present a wandering behaviour, some of them around a smooth annual seasonality and possibly following a trend. For this reason the stationarity assumption cannot be considered as given. I investigate the issue using the ADF (Dickey and Fuller 1979, Said and Dickey 1984) unit root test and the KPSS (Kwiatkowski, Phillips, Schmidt and Shin, 1992) stationarity test on the levels and on the first differences. The results of the tests, with the descriptive statistics of the variables in levels are reported in table 1. For coal and oil price both tests support the presence of a unit root, while for gas, electricity and carbon price they give opposite indications. In fact, both the null hypothesis of unit root and the one of stationarity are refused. On the contrary there is strong evidence that the first differences of all series are stationary (results not reported here but available on request from the author). This behaviour is typical of gas and electricity price series, which often present a dynamics that is borderline between stationary and unit root processes (for an illustration see Haldrup and Nielsen, 2006). In this context I decide to model all series as non-stationary following Hendry and Juselius (2000). They suggest that "even though a variable is stationary, but with unit root close to unity […] it is often a good idea act as if there are unit roots to obtain robust statistical inference". I point out that here the goal of the VAR analysis is to determine the interrelationships among the variables and to derive the impulse response functions, not to obtain a valid estimate of the parameters. For this reason, following Sims, Stock and Watson (1990) I estimate model (1) on the levels even if the variables are I(1), since conducting the analysis on the first differences potentially hides important information concerning the co-movements of the data (i.e. cointegrating relationships).

As introduced in section 2.2, the relation between temperature and electricity price is non-linear and 'U' shaped. In order to define the thresholds where the relationship reverts, it is possible to analyse the scatter plots between temperature and electricity prices[6]. Observing figure 2, I define the thresholds as 45^{O} F and 65^{O} F for Germany and 55^{O} F and 65^{O} F for United Kingdom.

In order to estimate the model (1) I follow a two step procedure. In the first step the unrestricted model is estimated and then, following a 'general to specific' approach, a sequential elimination of non-significant regressors is implemented. This is done comparing the reduction of the AIC criteria excluding different regressors as illustrated in Brüggemann and Lütkepohl (2001).

[6] Instead of actual temperature, I considered the mean temperature between yesterday and today, in order to take into account temperature inside buildings does not react instantaneously to a change in the atmospheric temperature.

The results of the selected model for Germany, estimated using GLS, are presented in table 2. The analysis of the residuals[7] suggests a good specification: there is no evidence of un-modelled residual autocorrelation and the parameter estimates are stable according to the CUSUM test at 5% significance level. Even if there is still an indication of Arch effect in the residuals of the gas and of the carbon price equations (this finding is confirmed by the CUSUM of squared test) this is not likely to be a serious problem (see Hendry and Juselius, 2000). All the estimated parameters of the correlation matrix Σ are very low, and none of them is statistically significant. This means that the instantaneous effects have been well captured by the exogenous variables; for this reason the residual component assumes a structural, economic meaning. Examining the parameters of the interactions among the endogenous, a triangular structure emerges: carbon prices influences both future gas and electricity prices, gas prices influences only future electricity prices and electricity prices influences none of the other series. From this findings carbon emission permits price can be considered as strongly exogenous for the parameters of the equations of the other series. This is consistent with the hypothesis that CO_2 is traded on a larger market (the EU) compared to the one (Germany) for gas and electricity. For this reason shocks in the German electricity or gas market alone are not strong enough to influence the behaviour of carbon price traded in the EU.

The impulse response function of electricity prices to a shock on carbon prices and to a shock on gas prices are compared in figure 3. Both shocks produce a similar effect in the first days but, the gas price shock is completely absorbed after two weeks time, whether the shock on carbon price is persistent, showing a significant marginal effect even after one month. This can be explained considering that the gas market is a relatively mature one. For this reason, the equilibrium price of gas is clear in the agent's minds and an unexpected shock, if not too intense, is re-absorbed fast. On the contrary the carbon emission market is immature, and the uncertainties regarding the equilibrium price of carbon are still substantial. A shock is perceived as very persistent and also persistent and significant is its effect (i.e. its pass-through) on electricity and gas prices. Figure 4, in which is compared the effect on gas prices of a shock on gas and of a shock on carbon, is consistent with that intuition. The gas price shock is absorbed after one week, whether the carbon one persists.

The estimated model for the UK, in table 3, illustrates a somewhat different situation. From the analysis of the residuals the models seems to present no sign of misspecification, but in the correlation matrix Σ a few elements are statistically significant, particularly the one regarding the correlation among the electricity and the gas equation. This feature suggests that the two markets are more respondent to each others signals that in the German case and, hence, more interconnected.

[7] For an illustration of the specification and of the residual tests implemented in this paper see, for example, Johnston and DiNardo, 1997.

Since residuals are (slightly) cross-correlated, the impulse response function, shown in figures 4 has to be evaluated cautiously. The picture is rather different to the German case, since gas prices do not seems to be significantly affected by a shock on carbon prices (impulse response function not reported here, but this feature can be noticed observing table 3). On the contrary, a gas price shock affects both electricity and carbon prices. A possible reason is that in the UK the quantity of electricity produced by gas-fired power stations in rather large, around 40%, and the main initiative, in order to fulfil the Kyoto target, has been to switch from coal to gas. Switching becomes more expansive if gas prices are high, and this is reflected in carbon prices.

4 Conclusions and ongoing research

Uncovering the interactions between carbon, electricity and gas price presents an inherent complexity, mainly because of the bilateral direction of causality. I showed how, through a simple VAR approach, it is possible to bring some light on this issue, and predict, inter alia, the reaction of electricity price (i.e. the pass-through) to a shock on carbon prices and on gas prices. As shown in section 3, these shocks, even though applied with the same magnitude, produce fundamentally different effects.

Even though useful for those purposes, the VAR approach does not allow to estimate the structural economic relationships that relate the price of the three commodities. In order to achieve this task I am defining a simple economic model that identifies the supply and demand function for electricity, the supply and demand function for gas and the demand function for carbon emission permits (since, as explained in section 2, the supply is essentially fixed). As shown in section 3, the variables do not conform to the stationarity assumption, a feature that must be taken into account in order to obtain robust inference[8]. This issue can be solved with a two step procedure. In the first step the structural, long run relationships are estimated through the cointegration technique, developed in Johansen (1988, 1990). As illustrated in Boswijk (1995), Johansen (1995) and Davidson (1998) when these restrictions are based on economic theory one can interpret the cointegrating relation as long-run behavioral relationships, with direct economic meaning. In the second step the short-run relationships are modeled as a traditional simultaneous equation model that embeds an error-correction term and estimated using 3SLS (this approach has been implemented, for instance, in Fezzi and Bunn 2005 in order to estimate the supply and demand

[8] One of the basis of classical econometric theory is the stationarity of the variable considered in the analysis (Hendry and Juselius, 2000). Under this condition classical statistical inference is valid, while assuming this postulation when it doesn't hold can induce serious statistical mistakes. Modelling non-stationary variables as they would be stationary invalidates in most cases all the inference procedure leading to a problem known in literature as spurious regression or "nonsense correlation", with extremely high correlation often found between variables for which there is no causal relation. In such conditions many statistical inference tools such as the Student's t, the F test and the R^2 are no longer valid. For a detailed and extensive analysis we suggest to refer to the wide literature available, for example, Granger and Newbold (1974), Hendry (1980), Phillips (1986) and Hendry and Juselius (2000).

function for electricity in the PJM market). The resulting model provides a considerable amount of information. For instance the elasticities of the gas and of the electricity supply curves to carbon price are directly estimated, and also the elasticity of carbon permits demand to coal, gas and electricity prices. The latter gives important indication in order to derive the shifts of the marginal cost of abatement curve due to the variation of the prices in the energy sector.

This analysis will be undertaken also on forward prices, since they are likely to be more related to the fundamental structure of the market, whereas spot (day-ahead) markets are more unstable, dominated by trading strategies and unexpected shocks. Furthermore, the price of carbon permits can be naturally interpreted as a future market with delivery date the 30th of April 2006.

References

Barreto L., Kypreos S. (2004) Emission trading and technology deployment in an energy-system "bottom-up" model with technology learning, European Journal of Operational Research, vol. 158, pp. 243-261

Bernanke B.S. (1986) Alternative explanations of the money-income correlation, Carnegie-Rochester Conference Series on Public Policy, Autumn 1986, pp. 49-100

Blanchard O.J., Quah D. (1986) The dynamic effects of aggregate demand and supply disturbances, American Economic Review, vol. 79, n. 4, pp. 655-673

Böhringer C. (2002) Industry-level emission trading between power producers in the EU, Applied Economics, vol. 34, n. 4, pp. 523-533

Boswijk H.P. (1995) Efficient inference on cointegration parameters in structural error correction models, Journal of Econometrics, vol. 69, 1995, pp. 133-158

Brüggemann R., Lütkepohl H. (2004) Structural vector autoregressive modelling and impulse responses, in H. Lütkepohl and M. Krätzig (eds), Applied Time Series Econometrics, Cambridge University Press

Bunn D.W. (2000) Forecasting load and prices in competitive power markets, Proceedings of IEEE, vol. 88, No. 2, pp. 163 -169

Criqui P., Viguier L.L. (2000) Kyoto and technology at world level: cost of CO2 reduction under flexibility mechanism and technical progress, International Journal of Global Energy Issues, vol. 14, pp. 155-168

Davidson J. (1998) Structural relations, cointegration and identification: some simple results and their application, Journal of Econometrics, vol. 87, 1998, pp. 87-113

Dickey D.A., Fuller W.A. (1979) Distribution of the estimators for autoregressive time series with an unity root, Journal of the American Statistical Association, vol. 74, 1979, pp. 427-431

Engle R. F., Granger C. W. J., Rice J. Weiss A. (1986) Semiparametric estimates of the relation between weather and electricity sales, Journal of the American Statistical Association, vol. 81, 1986, pp. 310-320

European Commission (2003) Directive 2003/87/EC of the European Parliament and of the Council of 13 October 2003 establishing a scheme for greenhouse gases emission allowance trading within the Community and amending Council Directive 96/61/EC. OJ L275

European Commission (2005) Review of the EU Emissions trading scheme, Survey Highlights, November 2005, European Commission Directorate General for Environment

Fezzi C., Bunn D.W. (2005) An error-correction, simultaneous equation model to estimate the demand and the supply curves in electricity markets, London Business School, working paper

Granger C.W.J., Newbold p. (1974) Spurious regression in econometrics, Journal of Econometrics, vol. 2, 1974, pp. 111-120

Haldrup N., Nielsen M.O. (2006) A regime switching long memory model for electricity prices, Journal of Econometrics (forthcoming)

Hall P. (1992) The bootsrap and Edgeworth expansion, Springer, New York

Hamilton J. (1994) Time series analysis, Princeton University Press, Princeton, New Jersey

Hauch J. (2003) Electricity trade and CO2 emission reduction in the Nordic countries, Energy Economics, vol. 25, pp. 509-526

Hendry D.F. (1980) Econometrics: Alchemy or Science?, Economica, vol. 47, 1980, pp. 387-406. Reprinted in Hendry D.F: (1993) Econometrics: Alchemy or Science?, Oxford, Blackwell Publishers

Hendry D.F., Juselius K. (2000) Explaining cointegration analysis: Part I, The Energy Journal, vol. 21, 2000, pp. 1-42

Huntington H.G., Weyant J.P (2004) Modeling energy markets and climate change policy, In Cleveland, C.J. et al. Encyclopedia of Energy, pp. 41-53, Academic Press / Elsevier Science

Knittel C.R., Roberts M.R (2005) An empirical examination of restructured electricity prices, Energy Economics, vol. 27, pp. 791-817

Kwiatkowski D., Phillips P.C.B, Schmidt P., Shin Y. (1992) Testing the null hypothesis of stationarity against the alternative of a unit root, Journal of Econometrics, vol. 54, 1992, pp. 159-178

Johansen S. (1988) Statistical analysis of cointegration vectors, Journal of Economics, Dynamics and Control, vol. 12, 1988, pp. 231-254

Johansen S. (1991) Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models, Econometrica, vol. 59, No. 6, 1991, pp. 1551-1580

Johansen S. (1995) Identifying restriction of linear equations with applications to simultaneous equations and cointegration, Journal of Econometrics, vol. 69, pp. 111-132

Johnston J., DiNardo J. (1997) Econometric methods, McGraw Hill

Linares P., Santos F.J., Ventosa M., Lapiedra L. (2006) Impacts of the European emission trading directive and permit assignment methods on the Spanish electricity sector, The Energy Journal, vol. 27, No 1, pp. 79 - 98

McKibbin W., Ross M, Shackleton R., Wilcoxen P.J. (1999) Emission trading, capital flows and the Kyoto Protocol, The Energy Journal, Special Issue: The costs of the Kyoto Protocol, pp. 287-334

Phillips P.C.B. (1986) Understanding spurious regression in econometrics, Journal of Econometrics, vol. 33, pp. 331-340

Said S.E., Dickey D.A. (1984) Testing for unit roots in autoregressive moving average models of unknown order, Biometrika, vol. 71, 1984, pp. 599-608

Sims C. (1980) Macroeconomics and reality, Econometrica, vol. 48, n. 1, pp. 1-48

Sims C. (1986) Are forecasting models usable for policy analysis? Federal Reserve Bank Minneapolis, Quarterly Review (winter 1986), pp. 2 - 16

Sims C., Stock J., Watson M.W. (1990) Inference in linear time series models with some unit roots, Econometrica, vol. 58, pp. 113-144

UNFCC (1998) The Kyoto protocol to the convention on climate change, United Nations

Appendix I: Figures

Figure 1: UKPX electricity price, EEX electricity price, NBP gas price, TTF gas price, carbon emission permit index price, coal ARA price, Oil price and temperature in Munich. All variables except temperature in their natural logarithms

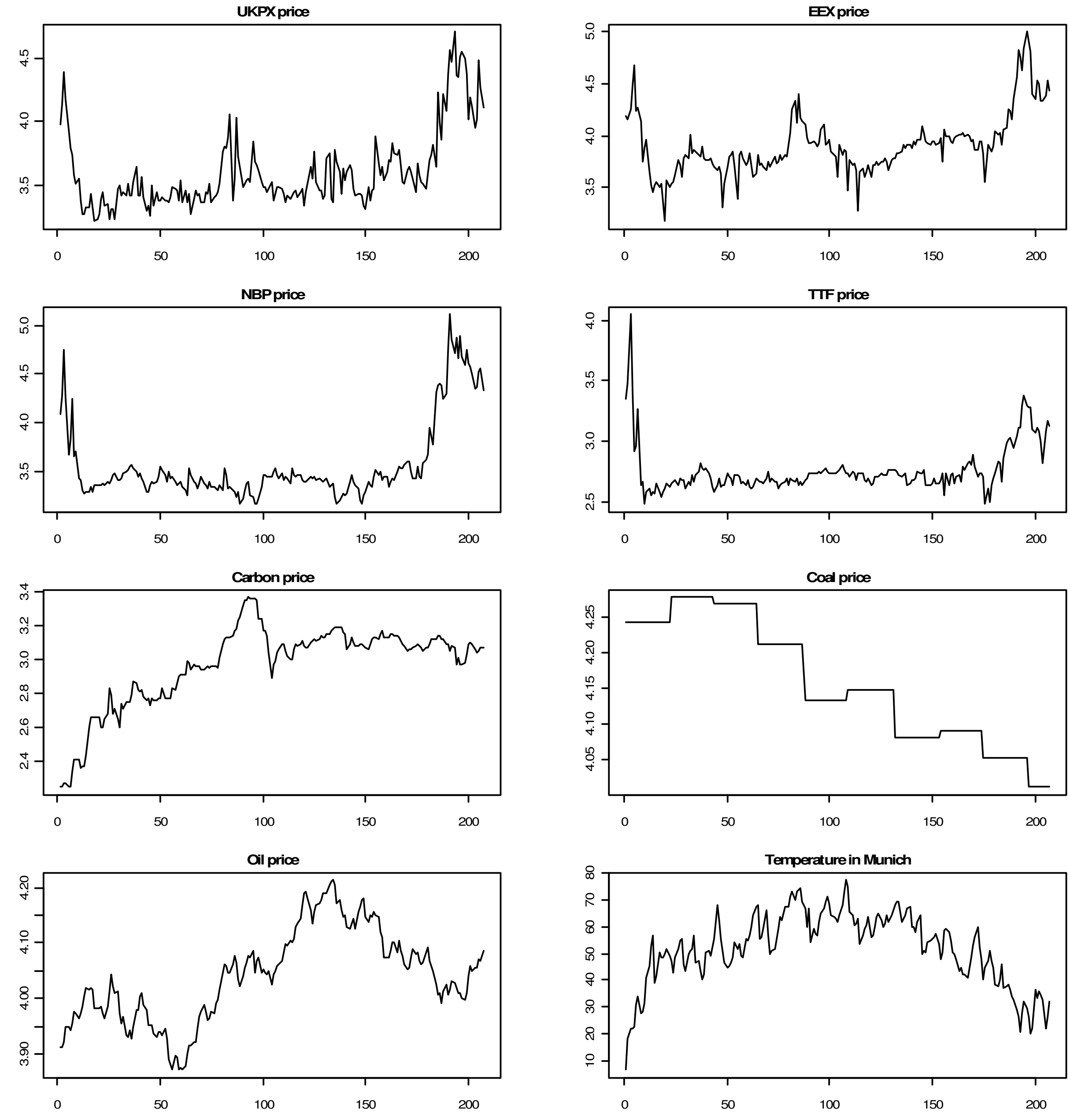


Figure 2: Relationship between atmospheric temperature (two terms moving average) and electricity price

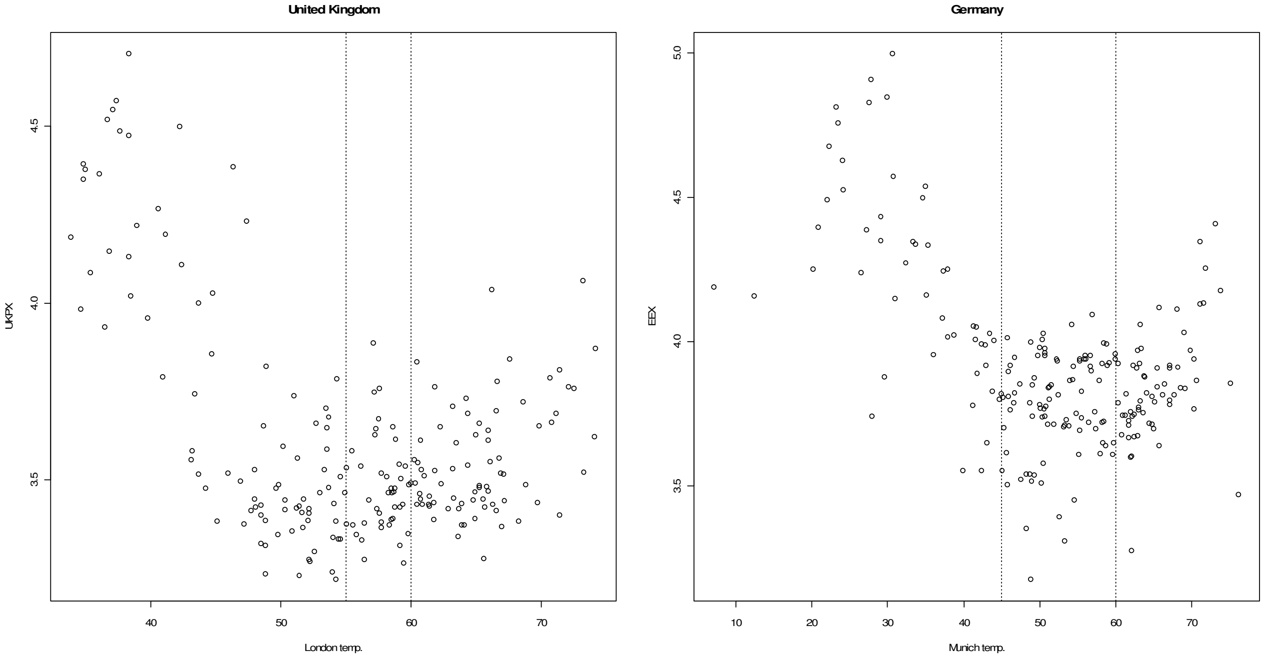
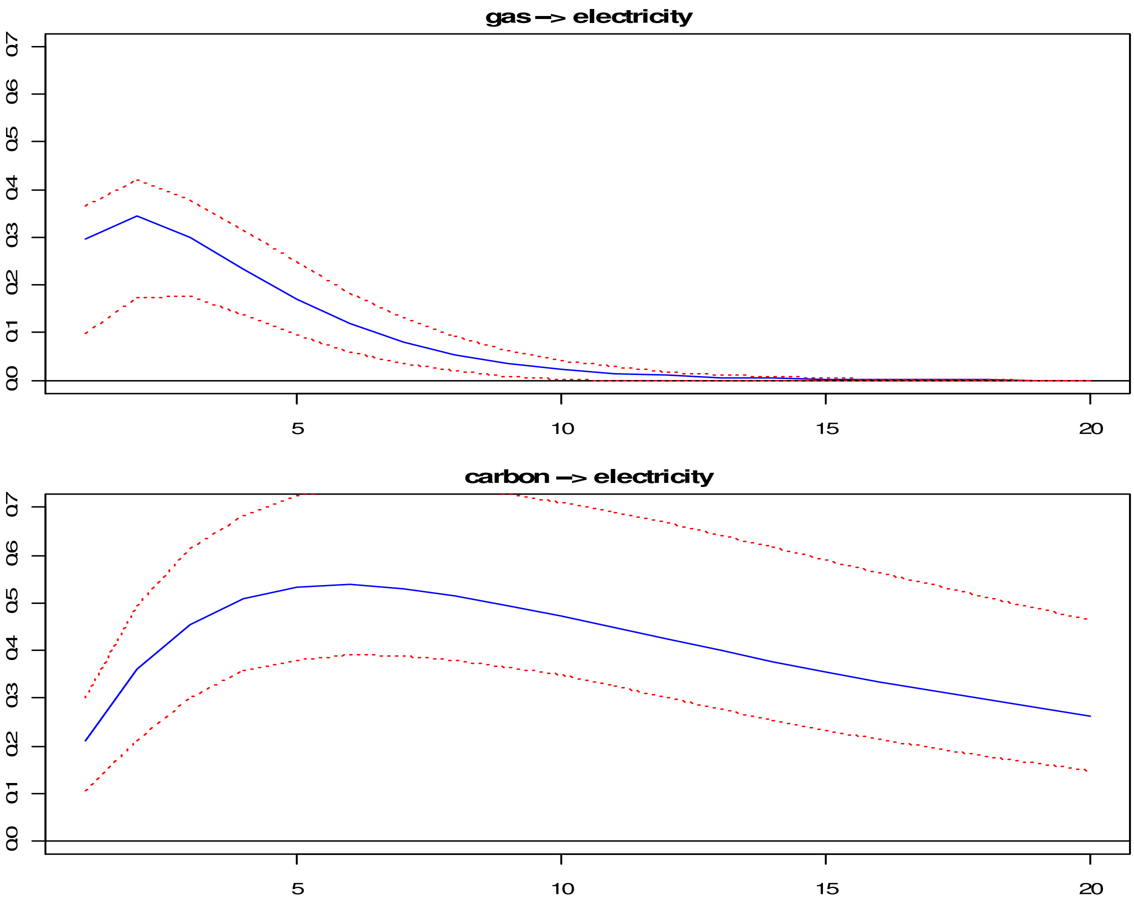


Figure 3: Impulse response function, effects on electricity prices (EEX) of one unit shock on gas prices (TTF) and of one unit shock on carbon prices.



Note: Bootstrapped 95% confidence intervals as introduced by Hall (1992)

Figure 4: Impulse response function, effects on gas prices (TTF) of one unit shock on gas prices (TTF) and of one unit shock on carbon prices.

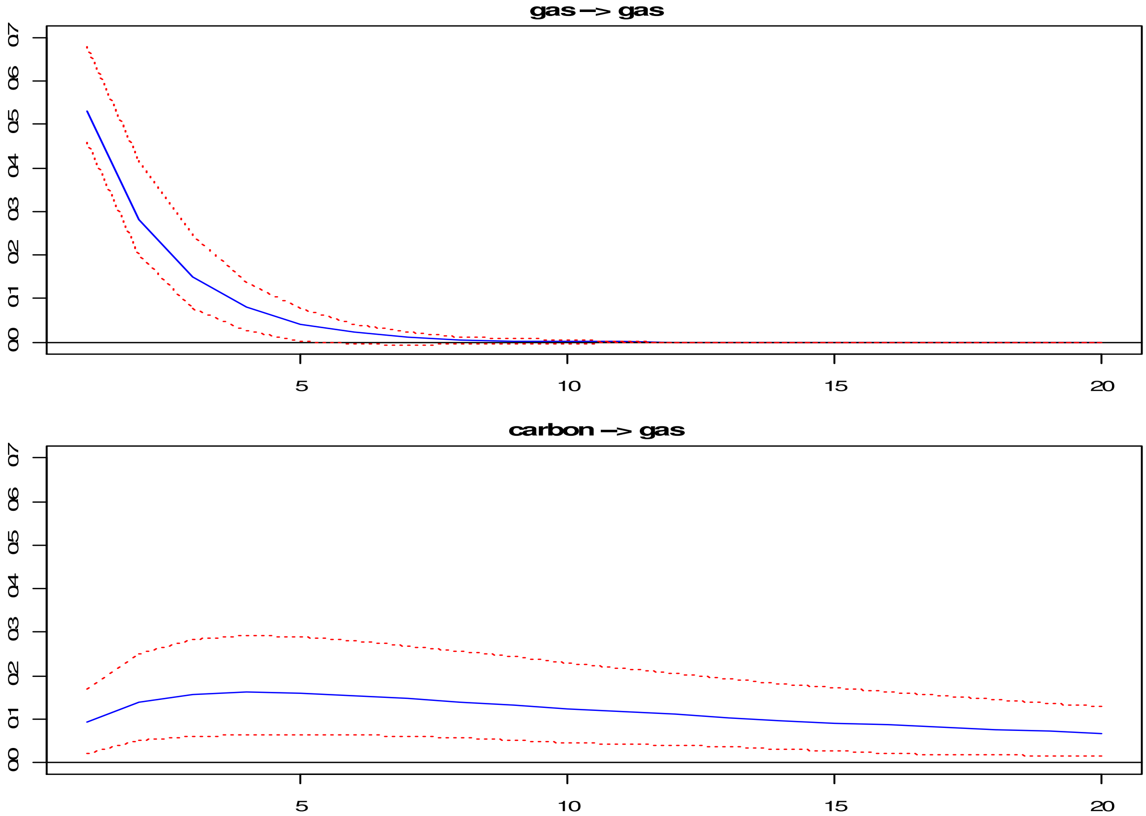
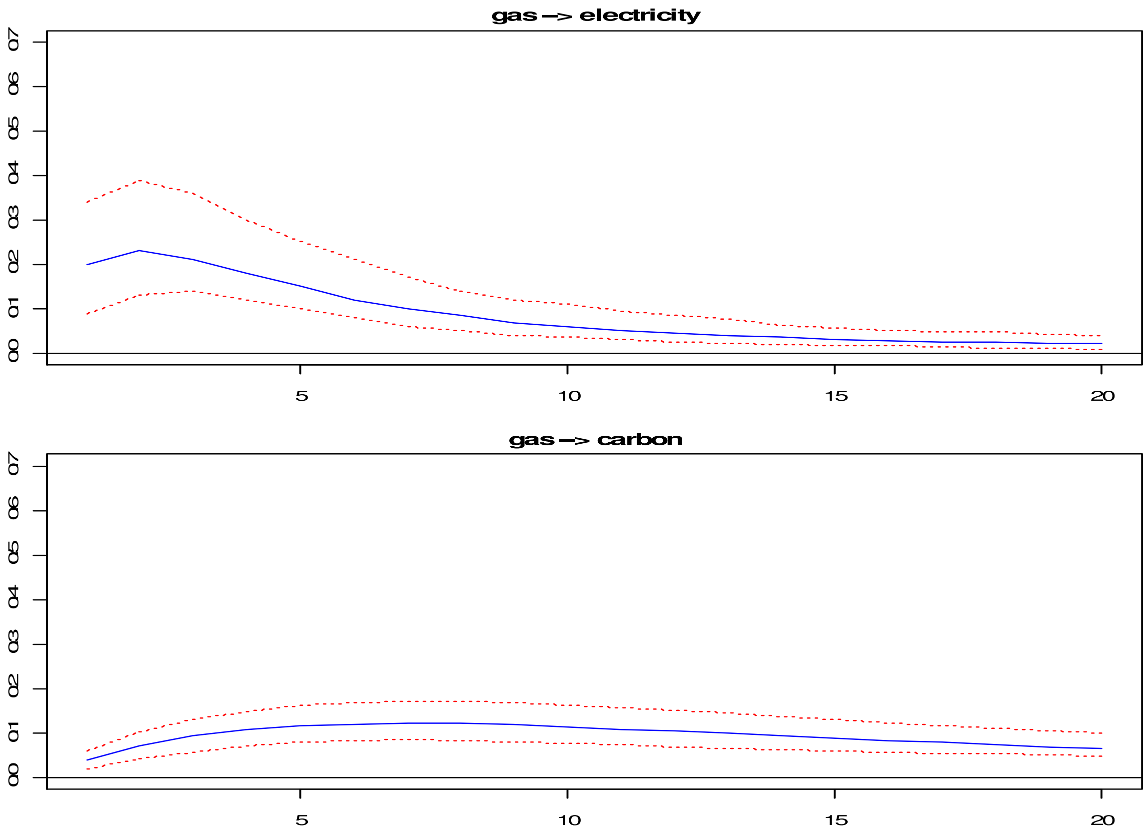


Figure 4: Impulse response function, effects on electricity prices (UKPX) and on carbon prices of one unit shock on gas prices (NBP).



Appendix II: Tables

Table 1: Descriptive statistics and unit root test of UKPX electricity price, EEX electricity price, NBP gas price, TTF gas price, carbon emission permit index price, coal ARA price, Oil price and temperature in Munich. All variables except temperature are in their natural logarithms.

Variable	Skewness	Kurtosis	Trend	ADF	(lags)	KPSS
Carbon	-1.2124	4.2117	0	-3.51**	4	2.160***
Coal	0.006	1.6194	1	-2.95	0	0.210***
EEX	1.1136	5.0147	1	-4.42***	6	0.247***
UKPX	1.5988	5.0568	1	-4.05***	2	0.333***
TTF	2.7616	13.4778	1	-5.05***	1	0.282***
NBP	1.984	5.8154	1	-3.06***	6	0.520***
Oil	0.0746	2.271	1	-1.57	4	0.460***
London t.	-0.4172	2.5281	1	-0.43	18	0.728***
Munich t.	-0.7174	3.2015	1	-0.31	20	0.748***

Note: Trend indicates if it has been used a trend in the test;
The lag length for the KPSS test has been selected as 4(T/100)^1/4

Table 2: VAR model for German electricity price, gas and EU carbon prices. Estimated coefficients (t-stat in parenthesis), correlation matrix and residual tests

	Electricity price (EEX)	Gas price (TTF)	EU carbon price
EEX_{t-1}	0.627 [12.83]	--	--
TTF_{t-1}	0.297 [5.37]	0.532 [9.08]	--
EU Carbon $_{t-1}$	0.212 [4.44]	0.094 [3.25]	0.941 [50.14]
Temp. Cold $_t$	-0.006 [-2.19]	-0.014 [-5.76]	-0.014 [-1.74]
Temp. D Cold $_t$	0.292 [2.59]	0.591 [6.24]	-0.124 [-1.63]
Temp. Hot $_t$	0.006 [1.66]	--	0.002 [1.67]
Temp. D Hot $_t$	-0.442 [-1.74]	--	--
Oil $_t$	--	--	--
Coal $_t$	--	--	-0.077 [-1.48]
Const	--	0.967 [6.09]	--
Residual Correlations	1	0.085 1	0.074 0.064 1
Ljung-Box (2)	0.398	0.082	0.215
CUMSUM	passed	passed	passed
Arch LM (2)	0.153	0.000	0.009
CUMSUM - SQ	passed	failed	failed

Lag length selected with AIC criterion

Table 3: VAR model for United Kingdom electricity price, gas and EU carbon prices. Estimated coefficients (t-stat in parenthesis), correlation matrix and residual tests

	Electricity price (UKPX)	Gas price (NBP)	EU carbon price
$UPKX_{t-1}$	0.380 [6.45]	--	0.025 [1.57]
NBP_{t-1}	0.201 [3.38]	0.742 [13.72]	0.040 [2.64]
EU Carbon $_{t-1}$	0.163 [2.59]	--	0.929 [67.48]
Temp. Cold $_t$	-0.018 [-4.55]	-0.010 [-2.60]	0.005 [5.52]
Temp. D Cold $_t$	0.930 [4.33]	0.546 [2.82]	-0.291 [-5.51]
Temp. Hot $_t$	-0.011 [2.82]	--	--
Temp. D Hot $_t$	-0.683 [-2.74]	--	--
Oil $_t$	--	-0.467 [-2.91]	--
Coal $_t$	-0.274 [-1.52]	-0.840 [-4.53]	--
Const	2.127 [2.18]	6.261 [4.42]	--
Residual Correlations	1	0.250 1	0.146 0.049 1
Ljung-Box (2)	0.748	0.002	0.281
CUMSUM	passed	passed	passed
Arch LM (2)	0.0021	0.000	0.050
CUMSUM - SQ	failed	failed	failed

Lag length selected with AIC criterion