Causalities Between Carbon-Price Variations and Short-Run Deviations In Electricity Prices

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Introduction

- The European authorities set up the EU ETS which concerns predominantly the electricity-generation sector.
- The main objective of the EU ETS is to encourage the industry's biggest emitters to reduce their carbon emissions and invest in clean technologies.
- The scheme is organized in three phases: 2005-2007, 2008-2012 and 2013-2020.
- Unlike the pilot phase, Phase 2 allows "Banking" permits for subsequent periods.

The French and German electricity-price causalities

- France and Germany are two neighbouring countries with different energy mixes.
- Kirat & Ahamada (2011) find high and significant conditionnal correlation between day-ahead electricity prices in both countries.

Carbon-price and electricity-price causalities

Economic theory allows for different possibilities of causal links between electricity and carbon prices. The two most important theories are:

- The abatement cost theory: causality runs from carbon-price towards electricity-prices
- The capture rent theory: causality runs from electricity-prices toward carbon-price

The research question

This article studies the causalities between the short-run deviations in the French and German day-ahead electricity prices and carbon-price variations. This includes two main questions:

- What is the impact of carbon-price on the short-run relationship between electricity-prices in France and Germany?
- Do deviations in electricity prices in France cause those in Germany or vice versa?

We use the Qu and Perron's approach of structural change in multivariate model (Econometrica, 2007)

Data

The data used are weekdays frequency and run from July 4th, 2005 to December 28th, 2007 for the first phase of the EU ETS, and from March 3rd, 2008 to June 21th, 2010 for phase II. The data include:

- Day-ahead base load electricity prices on the French and German electricity stock exchanges (€/Mwh).
- The carbon spot price of the Bluenext stock exchange (€/ton).

Data preprocessing

- In order to get the gap between the verified electricity prices and their long-run paths, we apply the HP filter on the French and German natural logarithm electricity-price series. The gaps are interpreted as short-run deviations of electricity prices from their long-run trajectories. Smaller are the gaps and more stable are the prices around their long-run paths.
- We seasonally adjust the gap series using daily dummies.
- We take the first difference of the logarithm of carbon spot price.

Econometric modeling

For each regime j, $j = 1, ..., m+1$, we consider the following VAR model as in Qu and Perron (2007)

$$\begin{pmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \end{pmatrix} = \begin{pmatrix} \pi_{j0}^{1} \\ \pi_{j0}^{2} \\ \pi_{j0}^{3} \end{pmatrix} + \sum_{i=1}^{p} \begin{pmatrix} \pi_{ji}^{11} & \pi_{ji}^{12} & \pi_{ji}^{13} \\ \pi_{ji}^{21} & \pi_{ji}^{22} & \pi_{ji}^{23} \\ \pi_{ji}^{31} & \pi_{ji}^{32} & \pi_{ji}^{33} \end{pmatrix} \begin{pmatrix} y_{1t-i} \\ y_{2t-i} \\ y_{3t-i} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{pmatrix}$$

where $t \in [T_{j-1}+1, T_j]$.

We estimate the parameters and the dates of breaks ($\hat{\pi}_j$ and $\hat{T}_j$).

Model selection criteria by Kurozumi and Tuvaandorj (2010)

Kurozumi and Tuvaandorj (2010) established the modified Akaike (AIC) and the modified Bayesian (BIC) information criteria.

$$MAIC = -2LL + 2 * (p_{\phi}^{all} + p_{\sigma}^{all}) + 6m$$

$$MBIC = -2LL + (p_{\phi}^{all} + p_{\sigma}^{all} + 2m) * \ln T$$

These criteria allows for model selection in the presence of non-linearities.

Table 1. Estimation results of break dates in VAR(1,2,5) for phase I

Dates of breaks	95% Confidence interval
October 26, 2005	October 21, 2005 - November 14, 2005
April 11, 2006	April 10, 2006 - April 18, 2006
July 27, 2006	July 19, 2006 - August 2, 2006
January 2, 2007	December 29, 2007 - January 10, 2007
April 30, 2007	April 3, 2007 - May 8, 2007
September 12, 2007	August 31, 2007 - November 6, 2007

Table 2. Estimation results of break dates in VAR(1 2 5) for phase II

Dates of breaks	95% Confidence interval
July 1, 2008	June 20, 2008 - July 24, 2008
October 20, 2008	October 10, 2008 - October 29, 2008
February 12, 2009	January 27, 2009 - February 17, 2009
June 3, 2009	May 27, 2009 - June 10, 2009
October 2, 2009	October 1, 2009 - October 7, 2009
January 12, 2010	January 4, 2010 - January 14, 2010

Using the euclidian distance (or the dmax distance) between the vectors of parameters of two consecutive regimes, one can rank the structural breaks depending on the magnitude of structural changes.

- Phase I: April 11, 2006 ; October 26, 2005 ; July 27, 2006 ; January 2, 2007 ; September 12, 2007 ; April 30, 2007.
- Phase II: October 2, 2009 ; January 12, 2010 ; October 20, 2008 ; February 12, 2009 ; July 1, 2008 ; June 3, 2009.

Table 3. Granger causality tests during phase I

Regime number	1	2	3	4	5	6	7
Granger causality tests (Prob > chi2)							
Fra ⟶ Ger	0.014	0.329	0.069	0.399	0.110	0.062	0.044
Carb ⟶ Ger	0.543	0.024	0.723	0.030	0.620	0.168	0.014
Ger ⟶ Fra	0.000	0.001	0.000	0.003	0.094	0.000	0.000
Carb ⟶ Fra	0.624	0.052	0.132	0.709	0.665	0.570	0.693
Ger ⟶ Carb	0.395	0.156	0.542	0.183	0.785	0.089	0.109
Fra ⟶ Carb	0.455	0.381	0.171	0.140	0.120	0.558	0.725
Log likelihood	345.31	396.84	117.16	293.52	197.07	172.05	47.30
Sum LL				1569. 3			
MAIC				-2598. 6			
MBIC				-1431. 1			

Table 4. Granger causality tests during phase II

Regime number	1	2	3	4	5	6	7
Granger causality tests (Prob > chi2)							
Fra $\longrightarrow$ Ger	0.380	0.002	0.205	0.688	0.470	0.173	0.300
Carb $\longrightarrow$ Ger	0.677	0.321	0.283	0.550	0.821	0.090	0.727
Ger $\longrightarrow$ Fra	0.000	0.000	0.000	0.000	0.000	0.112	0.000
Carb $\longrightarrow$ Fra	0.617	0.472	0.213	0.548	0.056	0.515	0.858
Ger $\longrightarrow$ Carb	0.427	0.888	0.940	0.441	0.168	0.503	0.735
Fra $\longrightarrow$ Carb	0.023	0.844	0.478	0.145	0.005	0.607	0.262
Log likelihood	324.50	324.36	260.82	293.32	393.76	139.86	524.91
Sum LL				2261.5			
MAIC				-3983.0			
MBIC				-2836.9			