A robust multivariate long run analysis of European electricity prices*

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Abstract

This paper analyses the interdependencies existing in wholesale electricity prices in six major European countries. The results of our robust multivariate long run dynamic analysis reveal the presence of four highly integrated central European markets (France, Germany, the Netherlands and Austria). The trend shared by these four electricity markets appears to be common also to gas prices, but not to oil prices. The existence of long term dynamics among electricity prices and between electricity prices and gas prices may prove to be important for long term hedging operations to be conducted even in countries where well established and liquid electricity derivatives markets are not present.

Since standard unit root and cointegration tests are not robust to the peculiar characteristics of electricity prices time series, we adapt and further develop a battery of robust inference procedures that should assure the reliability of our results.

Keywords: European electricity prices, Cointegration, Interdependencies, Equilibrium Correction model, Oil prices.

JEL classification: C15, C32, D44, L94, Q40.

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1 Introduction

Following reforms introduced in the organization of electricity markets almost everywhere, wholesale electricity prices are now determined in regulated (generally, Pool) markets where prices are strongly affected by the impossibility to arbitrage between time and space.

In Europe, the reorganization of the electricity industry has been driven by the first and the second Electricity Directives of 1996 and 2003, respectively. The two Directives set a series of common measures to be taken by member countries in order to modify the entire architecture of their national markets. At the same time the European Commission is presently trying to implement a series of projects (such as new cross-border lines and common regulation of cross-border trade) to favour the creation of a truly common electricity market in the future.

While the newly created national wholesale markets show several important institutional similarities (same market design and homogenous regulation of cross-border trade) they still appear to be characterized by equally important differences in the physical (number and size of generation units) and technological structure (mainly, the sources of electricity generation) of their generation industries. Then, when one looks at the behaviour of the time series of prices generated in the European markets, it is hard to interpret similarities and differences in their dynamics and to attribute them to the prevalence of the institutional analogies or to the persistence of the structural diversities. Yet, an analysis of this kind is important to evaluate the state of the integration process of the European markets and the factors affecting their interdependency. Moreover, since electricity derivative markets are not equally developed in the different European countries, finding common trends in electricity prices may expand the choice of hedging strategies in those countries where these types of financial markets are still lacking.

Still, despite the aforementioned regulation similarities and the existence of physical interconnections that allow a significant cross-border trade among countries, post-reform European price series have generally been studied in isolation and the issue of the interdependency in the price dynamics of neighbouring markets has largely been ignored. Indeed, to our knowledge no study to date has examined long run interdependencies among electricity prices at the European level. Filling this gap is the primary motivation of this paper.

Here we conduct a multivariate dynamic analysis of prices generated by six major European electricity pools (Germany, France, Austria, Netherlands, Spain and Nordic Countries) in order to test the hypothesis of integration among European prices and between electricity prices and gas/oil prices. The finding of integrated dynamics of electricity prices would indicate that the markets considered are evolving consistently with the European Commission projects. Poor or no integration would suggest that the national structural differences are still dominant and that they affect price behaviour more heavily than the common regulation framework.

Our findings indicate that France, Germany, the Netherlands and Austria share a common trend, while Spain and the Scandinavian market do not. The hypothesis of strong integration[1] (DeVany and Walls 1999a) is not rejected only for France and Germany, even though for normal hedging times the returns on Austrian and Dutch prices are still very close to those of Germany and France.

Since electricity prices data have peculiar characteristics that make standard unit root and cointegration tests unreliable, we implement and further develop a battery of inferential procedures that should make our findings very robust. Our results contradict many existing studies in which electricity prices are found (or held) mean reverting.

The paper is organized as follows. In Section 2 we present the main characteristics – both institutional and technical – of some wholesale European markets for which data are available. Section 3 contains a critical review of previous analyses of time series of electricity prices. In Section 4, we present our dataset which is given by hourly electricity prices recorded in the above markets and from which, to account for time spans disparities, a common sample of 260 weekly median observations is taken. Motivation for the use of weekly medians is also given. Section 5 explains the methodology used for the estimations and discusses in particular the procedures followed to test the results of the long-run analysis. Section 6 contains the results of the long run analysis and the relative tests. Section 7 concludes.

2 The European electricity markets

Electricity market reform was first introduced in Chile in 1987 and since then it has spread to many areas of the world. The England and Wales (E&W) Pool market of 1991 was the first European experience of a liberalized wholesale electricity market.

In all countries the liberalization of the electricity industry followed a number of similar key steps: the unbundling of previously vertically integrated activities (generation, transmission, distribution and retail supply); the introduction of new institutions such as wholesale and retail competitive markets, with free entry of generators and suppliers; the creation of an independent national regulator who guarantees third party access to transmission and distribution networks.

The reorganization and new regulation of the electricity industry have been driven by some major developments in the technology that took place in the 70s and 80s. The new combined-cycle gas turbine (CCGT) plants are relatively small sized (350 MW to 450 MW). They have short construction times and require small investments. Moreover, CCGT units are highly efficient and have lower marginal costs than old open-cycle gas turbine plants. It follows that CCGT plants operate in hours of both low and high demand, and during low-demand periods they adjoin their supply to that provided by hydro and nuclear plants, when the latter are present. Old gas plants, on the contrary, are mainly used for peak hours and to provide reserve. Both hydro and nuclear plants created a strong barrier to competition

[1] Same long run returns, see below in the paper.

since they are more capital-intensive. Moreover, the former are site constrained, whereas the latter are subjected to strict national legislation. As a result, CCGT plants have been considered able to break the entry barriers to the industry and therefore to attract new investment and to enhance the degree of competitiveness of the generation segment.

The new liberalized market structure requires the operation of a central mechanism for the continuous match of demand and supply. In the countries considered in our sample, the coordination problem has been solved by means of a competitive wholesale spot market or wholesale auction. All the electricity Pools we consider work as multi-unit uniform price auctions: generators and buyers submit hourly price/quantity offers which are aggregated by the market operator according to a standard merit order: increasing asked price and decreasing bid price. The equilibrium price and quantity are then determined by the standard crossing condition between supply and demand curves. Producers (Buyers) who ask (bid) a price smaller (higher) or equal to the equilibrium price are included in the production (delivery) program for the next day. The total quantity sold by all despatched units is paid the System Marginal Price (SMP), defined as the bid made by the marginal unit selected by the mechanism.

The above auction-based dispatching does not take transmission conditions into account, and so congestions may occur both in the internal market and across-border. The main feature of the mechanisms implemented to manage congestions is that they are market-based. The resolution of bottlenecks may be managed by the Transmission System Operator by splitting the markets into zones characterized by different equilibrium prices. In the congested area the price is higher than the one prevailing in the non-congested area. The determination of the different zones is managed differently across markets. For example, within Norway and at the interconnections between the Nordic countries, price mechanisms are used to relieve grid congestions, resulting in different Elspot area prices. In Austria, which is an important transit country, congestion on the network occurs because of a high quota of energy that goes through the lines in order to be delivered abroad. Therefore, the network capacity in this country is extremely valuable and, as a result, network access tariffs are settled at the highest level compared to other countries. On the contrary, within Sweden, Finland, and Denmark, grid congestion is managed by counter-trade purchases based on bids from generators.

Electricity can be generated in a variety of ways and using different technologies. The electricity markets considered in this paper differ significantly in their underlying production and cost structure. Therefore, in each country the shape and composition of the merit order of suppliers are influenced by the productive mix of the generating industry. Figure 1 shows the composition of total production according to generation sources for the European countries considered in the sample.

The Nord Pool comprises the four Scandinavian countries listed in Figure 1. It links together Norway, which is the founding country (1993), Sweden, which joined in 1996, Finland (1998), and the western part of Denmark (1999). We notice

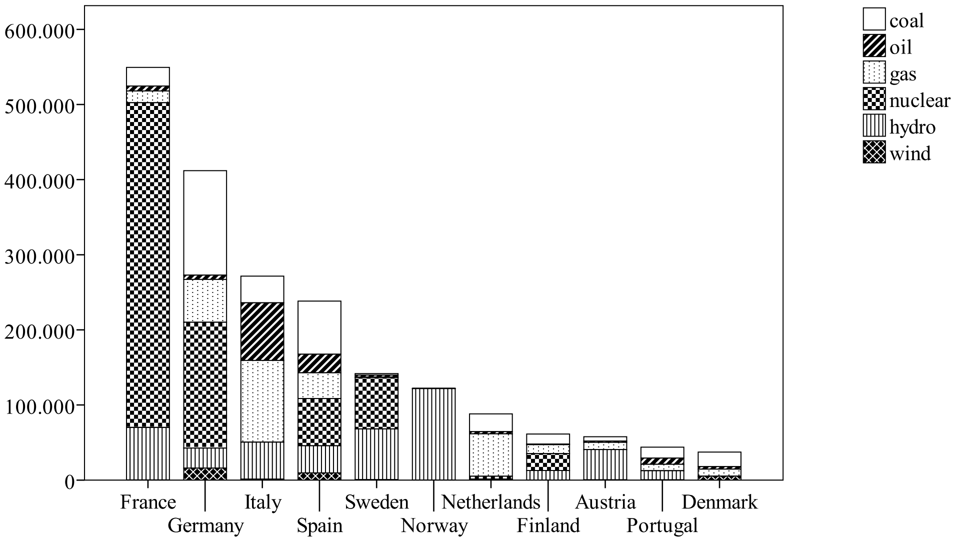

Figure 1: Production of electricity by technologies (average 2000-2004).

that a high percentage of Nord Pool's total production is generated by hydro and nuclear plants with limited recourse to gas and coal. In the Austrian market, hydro plants cover, on average, the 69% of total production. Germany, Spain, Sweden and especially France have a large nuclear production whereas Spain and France present similar figures on hydroelectric production. The Netherlands and Germany have a small quota of hydroelectric production. Finally, Italy and The Netherlands rely mainly on gas-fired plants.

Another important feature is the level of concentration of the industry. Indicators of the degree of concentration are the number of companies with a market share of at least 5% and the market share of the three largest producers.

Country	Largest Producer share by capacity	Totale share of the largest 3 producers
Austria (EXAA, 2002)	45%	75%
Scandinavia (Nord Pool, 1993)	15%	40%
France (Power Next, 2001)	85%	95%
Germany (EEX, 2002)	30%	70%
Italy (IPEX, 2004)	55%	75%
Netherlands (APX, 1999)	25%	65%
Spain (OMEL, 1998)	40%	80%

Source: Commission of the European Communities (2005)

Table 1: Level of concentration and liquidity multiple of European exchanges.

From Table 1, one can see that the French market is characterized by the highest level of concentration, with a dominant position of EDF. All the other markets listed in Table 1 appear to be fairly concentrated, with the exception of the Nord Pool. We may conclude that across European countries the level of concentration in generation is still high, and this creates the scope for market power and the ability to influence prices.

Contrary to expectations, the strong position of incumbent operators has not been eroded in a significant way by investments in generation made by new entrants. Complex planning procedures and the scarcity of suitable sites have also been named as reasons why the building of new power plants has not taken place.

Uncertainties associated with the power exchanges have also been considered as entry barriers. Generation is a key issue for competition in the European electricity markets. The generators, due to the characteristics of the electricity market (the non-storability of electricity, the high inelasticity of demand, a very wide spectrum of production costs and a price equal to the highest accepted offer (SMP) made in power exchanges), are able to influence prices through the use of generation capacity available to them, in particular by either withdrawing capacity (which may force recourse to more expensive sources of supply) or by imposing prices when their supply is indispensable in order to meet demand. The behaviour of generators can thus have a significant impact on the level of prices, even when the level of concentration is not very high.

Another relevant feature to be considered is the level of integration of national Pools. Indeed, there are interconnecting lines that allow for the cross-border exchange of electricity that is expected to flow from low price areas toward high price areas. The goal of the integration of European electricity markets will, in fact, be achieved when the energy flows determine a perfect convergence of Pool prices across European countries. Table 2 lists the existing interconnections among the exchanges considered and the status of the interconnection, namely the frequency with which congestion occurs. In fact, when congestion occurs in a particular hour, price convergence is not possible and the two local markets are separated.

Country (Export)	Country (Import)	Capacity Winter 2003-04	Capacity Winter 2003-04	Capacity Winter 2003-04	Congested
Powernext	EEX	2250	2550	2850	frequently
EEX	Powernext	4600	5600	5600	never
EEX	APX	3900	3800	3800	frequently
APX	EEX	2700	3000	3000	seldom
EEX	EXAA	1200	1600	1600	never
EXAA	EEX	1500	1400	1400	never
Nord Pool	EEX	1010	1150	1150	frequently
EEX	Nord Pool	920	1150	1150	occasionally
Omel	Powernext	600	1000	600	seldom
Powernext	Omel	1400	1400	1400	frequently

Table 2: Capacity (in MW) of interconnectors and frequency of congestion.

From the above considerations two main issues emerge. On the one hand, national electricity markets show great institutional similarities. All the countries considered present a similar market architecture designed to favour technological improvements and to increase consumer welfare through price decrease. On the other hand, however, we have also noticed that the national industries are characterized by persistent technological differences that may impinge upon electricity price convergence across Europe. This creates the scope for testing whether European electricity prices show clear signs of convergence or if they maintain a different "national" dynamic behavior.

3 The existing literature

Since the gradual reorganization of the electricity sector in Europe, the dynamics of European electricity prices have been analyzed by different researchers. The initial objective of these analyses was to characterize and explain the high degree of autocorrelation and seasonality of power prices and, in some cases, to address some salient issues useful to the valuation and hedging of power-based financial contracts.

Raw data show different kinds of seasonality (within a day, week, year) and phenomena such as high price-dependent volatility and leptokurtosis. However, all the analyses are univariate and concentrate on the short term dynamics of the time series. Indeed, most of the analysts conclude (Escribano *et al.* 2002, Haldrup and Nielsen 2006) or assume (de Jong and Huisman 2002, Deidersen and Trück 2002, Huisman and Mahieu 2003, Koopman *et al.* 2007) that prices are mean-reverting. Long memory is found by Haldrup and Nielsen (2006) and Koopman *et al.* (2007) in Nord Pool prices. In some cases (Byström 2005) price increments rather than price levels are analyzed, but without a formal long-term dynamics analysis.

As already mentioned, many authors conclude that European electricity prices are mean-reverting. The reasons are threefold. Firstly, the samples considered in the cited papers (late '90s - early '00s, with the exception of Nord Pool starting in 1993) cover a period of relatively moderate oil/gas price movements. Secondly, in testing for unit-roots, the peculiar features of electricity price dynamics (additive outliers, fat tails in the innovation process, heteroscedasticity, multiple seasonalities and periodicities) have not been sufficiently taken into consideration[2]. Thirdly, it is well documented by Franses and Haldrup (1994) and Arranz and Escribano (2004) that the ADF unit root test and Johansen's and ECM cointegration tests perform quite poorly when additive outliers and temporary changes are present. In fact, they are severely biased toward the rejection of the unit root hypothesis.

Bosco *et al.* (2006) too, use mean-reversion as a short-term approximation, since the Italian time series they analyze is too short to address the problem, but they suggest that electricity prices should show comovements with gas and oil, which are usually found to be integrated ($I(1)$).

[2]The paper by Escribano *et al.* (2002) is an exception, since they median-filter the data and bootstrap the unit-root test of Boswijk (2000), which allows for GARCH(1,1) dynamics.

Papers considering non-European data present mixed evidence: some authors find mean-reversion (Escribano *et al*. 2002, Knittel and Roberts 2005, Worthington and Higgs 2004), some find unit roots (DeVany and Walls 1999a, DeVany and Walls 1999b), while others are uncertain (Jerko *et al*. 2004, Park *et al*. 2006). In particular, Escribano *et al*. (2002) use average daily prices of several markets and propose a general and flexible model that allows for deterministic seasonality, mean reversion, jumps and conditional heteroskedasticity. They use six nested versions of their model to analyze price behavior in the above markets. Results indicate that AR(1) and GARCH (1,1) with jumps perform better than other versions. DeVany *et al.* (1999a,b) study electricity price behaviour for western U.S. markets and find that all of off-peak price series and most of peak price series are pair-wise cointegrated and, contrary to Banhot (2000), that prices show relatively rapid convergence with respect to external shocks. Park *et al*. (2006) examine relationships among 11 U.S. spot markets for the period going from February 1998 to December 2002, using peak working days firm prices (no week-end data). Their result suggests that the relationships among markets are not only a function of physical assets (e.g. transmission lines), but also a function of market rules and institutional arrangements as well as of factors (e.g. oil price) affecting in a similar or dissimilar way the markets or factors that are peculiar to each market (e.g. generation technology).

We believe that electricity prices should be $I(1)$, at least in those countries where a significant amount of electricity is generated using oil and gas. For countries in which gas and oil based generation is not significant, absence of mean-reversion could be found for at least two reasons: i) the SMP is often determined by thermal plants even in those countries where the production is dominated by other technologies (see Figure 1 and section 6.3), ii) all countries are interconnected and some interconnections have large capacities (see Table 2).

In the case unit roots were present in at least some of the price time series, it would be interesting to test for the presence of common trends. In particular, it would be interesting to assess if Europe, or at least a part of it, may be considered as one electricity market. For the determination of the degree of market-integration, we will draw from the terminology of DeVany and Walls (1999b): we will say that some electricity markets are strongly integrated if the long-run rate of price increases is (statistically) the same in each market. If, in addition, the price level is also (statistically) the same, we will say that the markets are perfectly integrated.

In the rest of this paper, we will subject all these hypotheses (unit root, cointegration, strong integration and perfect integration) to a robust analysis, using a large dataset and reliable testing techniques.

4 The data

For the empirical analysis we employ hourly time series of electricity prices registered in six major European wholesale markets: APX (Netherlands), EEX (Germany), EXAA (Austria), Nord Pool (Scandinavia), Omel (Spain), Powernext (France). Since hourly prices show strong within-day and within-week seasonalities and volatility clustering, we decided to use the logarithm of weekday medians (medians of 120 hourly observations) for the time period indicated in Figure 2. Working with weekly medians has several advantages. In fact, series formed with weekly medians can be used both in levels and in logs without altering their characteristics; they reduce the number and the impact of outlying observations, and, finally, they neutralize the strong seasonal movements within the day and the week. As for the outliers in particular, Arranz and Escribano (2004) demonstrate that median-filtering improves the size and power of unit root and cointegration tests.

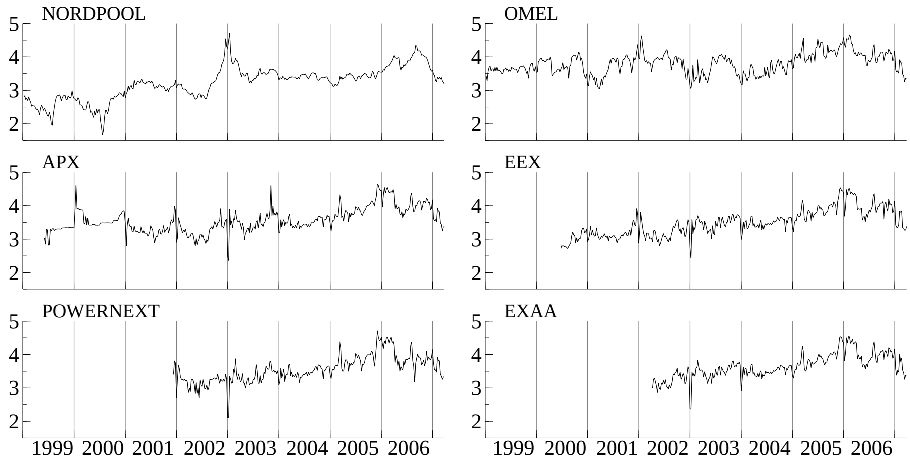

Figure 2: Weekly medians of log electricity prices (1st week of 1999 to 11th week of 2007).

Notwithstanding the de-noising effect of the median filter, it is clear from Figure 2 and from the large value of the kurtosis of weekly log-returns (see the lower half of Table 3) that additive outliers and fat tails are still important features to be accounted for.

Since the various time series are available for different time spans (Table 3), in every operation we used the longest feasible time span and the longest common sample (260 observation). In order to keep a due consistency among univariate and multivariate results, we base our discussion on the longest common sample only. All the relevant results still hold for the longer time-spans.

In Tables 3 and 4 we present descriptive statistics of weekly median prices and the correlation coefficients calculated across markets.

As one can see from Table 4, APX, EEX, EXAA and Powernext appear to be strongly correlated both in levels and in first differences. On the contrary, Omel shows quite a low degree of correlation with other series, whereas Nord Pool has the series with the smallest degree of correlation with the series of other markets.

Table 3: Descriptive statistics of weekly median prices and of their difference.

	NORD	OMEL	APX	EEX	POWER	EXAA
Mean	3.218	3.781	3.559	3.482	3.556	3.638
Median	3.296	3.792	3.485	3.466	3.511	3.607
Maximum	4.709	4.657	4.649	4.536	4.708	4.535
Minimum	1.668	3.044	2.363	2.430	2.106	2.365
Std. Dev.	0.492	0.308	0.373	0.404	0.397	0.368
Skewness	-0.195	0.208	0.510	0.396	0.235	0.121
Kurtosis	3.125	2.899	3.489	2.753	3.925	3.566
J-B prob	0.225	0.194	0.000	0.006	0.002	0.128
1st diff.	NORD	OMEL	APX	EEX	POWER	EXAA
Mean	0.001	0.000	0.001	0.002	0.000	0.002
Median	-0.003	-0.001	0.001	0.010	0.000	0.008
Maximum	0.433	0.556	1.527	1.156	1.222	1.110
Minimum	-0.570	-0.580	-1.129	-0.825	-1.153	-1.186
Std. Dev.	0.091	0.152	0.206	0.191	0.221	0.192
Skewness	-0.147	-0.013	0.150	-0.094	-0.227	-0.592
Kurtosis	8.527	4.439	15.075	9.183	10.029	13.170
J-B prob	0.000	0.000	0.000	0.000	0.000	0.000
1st obs.†	04/01/99	04/01/99	31/05/99	19/06/00	03/12/01	25/03/02
Sample	428	428	407	352	276	260
Source‡	DS	omel.es	DS	DS	powernext.fr	exaa.at

† Dates are in dd/mm/yy format and refer the first Monday. Last observation: 12/03/2007.

‡ DS stands for Datastream.

5 Tools for robust unit root and cointegration analysis

In order to explore the long-run dynamics and common features of time series with the aforementioned characteristics, we rely mainly on three tools: median filtering, robust parametric tests with unit roots as null hypotheses and robust semi-parametric tests with mean-reversion as null.

As mentioned before, median filtering has been proposed by Arranz and Escribano (2004) for robustifying unit-root and cointegration tests and has been applied by Escribano *et al*. (2002) to electricity prices.

The generalization of the approach to robustness of Huber (1981) and Hampel *et al*. (1986) to the case of integrated and cointegrated processes was carried out by Lucas in a series of articles (Lucas 1995a, 1995b, 1997, 1998a and Franses and Lucas 1998). In our analysis we use Lucas' robust pseudo-likelihood ratio (PLR) cointegration test based on the Student's t density. However, since its asymptotic distribution depends on nuisance parameters, we implement a bootstrap strategy based on the algorithms of Swensen (2006).

Since Lucas' PLR test is a generalization of Johansen's likelihood ratio, thus parametric and with unit roots under the null, we want to supplement its results by using a semi-parametric test with mean-reversion under the null. For scalar time series such a test is the KPSS of Kwiatkowski *et al*. (1992) and its recent

Table 4: Correlations among weekly median log-prices (above the diagonal) and weekly log-returns (below the diagonal).

	NORD	OMEL	APX	EEX	POWER	EXAA
NORD		-0.14	0.49	0.45	0.32	0.44
OMEL	0.00		0.50	0.53	0.59	0.54
APX	0.35	0.30		0.96	0.94	0.97
EEX	0.36	0.30	0.82		0.94	0.99
POWER	0.32	0.41	0.77	0.76		0.95
EXAA	0.37	0.35	0.84	0.92	0.82	

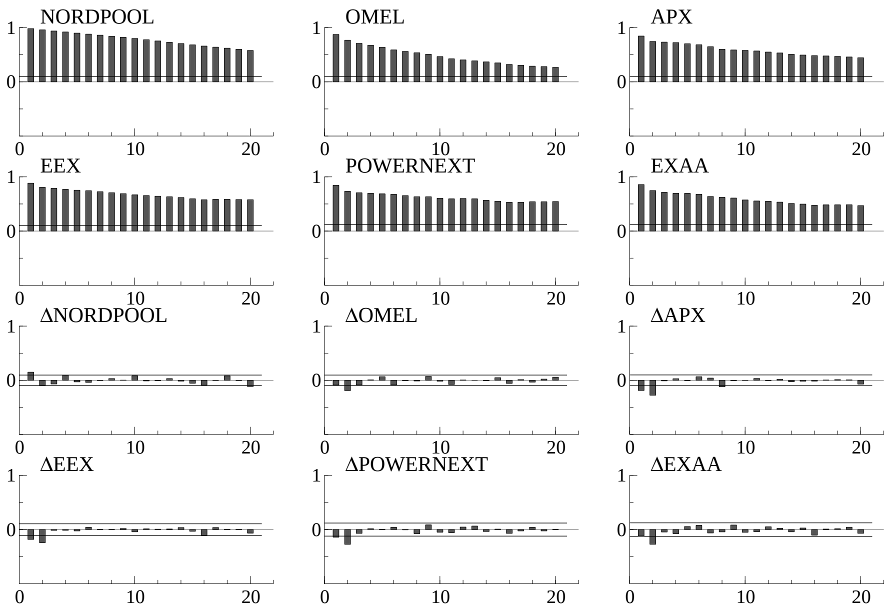

Figure 3: Sample autocorrelations of weekly median prices and of their difference.

robustification made by de Jong *et al*. (2007). Harris's (1997) principal components (PC) based test of cointegration may be seen as a multivariate generalization of the KPSS.

The following two subsections give some more insights into Lucas' and Harris' tests and into our implementation thereof. A further subsection is devoted to the generalization of de Jong *et al*.'s (2007) robust stationarity test.

5.1 Lucas' pseudo-likelihood ratio cointegration test

Consider the VAR$(p+1)$ model in VECM form

$$\Delta \boldsymbol{y}_t = \boldsymbol{\Pi} \boldsymbol{y}_{t-1} + \boldsymbol{\Gamma}_1 \Delta \boldsymbol{y}_{t-1} + \ldots \boldsymbol{\Gamma}_p \Delta \boldsymbol{y}_{t-p} + \boldsymbol{\Psi} \boldsymbol{D}_t + \boldsymbol{\varepsilon}_t \tag{1}$$

where $\boldsymbol{y}_t$ and $\boldsymbol{\varepsilon}_t$ are column vectors of dimension k, Δ is the first difference operator, $\Delta \boldsymbol{y}_t = \boldsymbol{y}_t - \boldsymbol{y}_{t-1}$, $\boldsymbol{\Pi}$, $\boldsymbol{\Gamma}_1, \ldots, \boldsymbol{\Gamma}_p$, are $(k \times k)$ parameter matrices, $\boldsymbol{D}_t$ is a matrix of deterministic regressors (usually a constant and a linear trend), and Φ a matrix of parameters. If $\boldsymbol{\varepsilon}_t$ is an i.i.d. random sequence with zero mean, positive definite covariance matrix $\boldsymbol{\Sigma}$ and density $f(\boldsymbol{\varepsilon}_t)$, model (1) may be estimated with and without reduced rank restrictions on $\boldsymbol{\Pi}$ by conditional maximum likelihood and the hypothesis $\mathrm{H}_0 : \mathrm{rank}(\Pi) \leq r$ tested against $\mathrm{H}_1 : \mathrm{rank}(\Pi) = k$ using the LR statistic.

If $f(\cdot)$ is a multivariate normal density, than the estimators and the test statistic have analytical forms[3] and the likelihood ratio (Johansen's Trace Test) has a non-standard asymptotic distribution, which does not depend on nuisance parameters (Johansen 1988, 1991).

If on the contrary $f(\cdot)$ is non-normal and the likelihood is correctly specified, then the LR statistic has a non-standard distribution depending on a set of nuisance parameters (Lucas 1997). When the likelihood function is misspecified, the asymptotic distribution depends on a further set of nuisance parameters (Lucas 1997). Since the asymptotic distribution of the test statistic has no closed form, critical values should be obtained by numerical simulation, but the presence of several nuisance parameters makes this solution unfeasible[4]. Lucas (1997) and Franses and Lucas (1998) provide conservative critical values based on Student's *t* distributions. Using this values generally leads to undersized tests, but under the presence of additive outliers and fat tails the power compares favorably with respect to Johansen's test for a large region of the parameter space (Lucas 1998a, p.196).

A second problem that arises when non-normal likelihoods are used, is that estimates are no more available in closed form. However if the pseudo-likelihood can be expressed as a treatable Gaussian mixture, as for example Student's *t*, then it is possible to implement an EM algorithm. Since we based our PLR tests on Student's *t* distribution, we adapted Little (1988) and Lange *et al.* (1989) to our case of cointegrated VECM models.

Let ν be the degree of freedom of the Student's distribution. We estimate the VECM parameters using Johansen's procedure and then we use these results to initialize the following EM iterations:

E. Given the estimates of the last step, compute the sequence

$$w_t = \frac{\nu + k}{\nu + \hat{\boldsymbol{\varepsilon}}_t' \hat{\boldsymbol{\Sigma}}^{-1} \hat{\boldsymbol{\varepsilon}}_t}.$$

M. Then estimate the parameters of equation (1) using Johansen's procedure after having multiplied by w_t the variables on both side of the equal sign. If

[3] If we are willing to consider the single value decomposition (SVD) an analytical tool.

[4] The nuisance parameters could be consistently estimated, and the asymptotic distribution could be simulated using these estimates, but as noted by Lucas (1997, p.157) this solution leads to poor approximations in finite samples.

the pseudo-likelihood increment with respect to last iteration is greater than a predetermined tolerance, go back to step *E*, otherwise stop the iteration.

Similar algorithms may also be used with other types of re-weighting functions, not directly linked to the Gaussian mixtures (Maronna *et al.* 2006, Sec. 6.3); the conditions under which they converge to a unique solution may be found in Tatsuoka and Tyler (2000).

In order to overcome the problem of nuisance parameters in the asymptotic distribution of the LR statistic, we implemented the Bootstrap algorithm 1 in Swensen (2006), who analyzes its convergence properties under Johansen test's conditions. Our version of this bootstrap strategy may be summarized by the following four steps. For $r = 0, 1, \ldots, k-1$,

1. estimate the unrestricted model (rank $= k$) under Student's t innovations using the above EM algorithm, and compute the relative residuals $\hat{\varepsilon}_{p+2}, \ldots, \hat{\varepsilon}_T$;
2. estimate the reduced rank (rank $= r$) model under Student's t innovations using the above EM algorithm;
3. generate bootstrap samples using $y_1, \ldots, y_{p+1}$ as initial values, the parameters of the restricted model obtained at step 2., and shocks re-sampled from $\hat{\varepsilon}_{p+2}, \ldots, \hat{\varepsilon}_T$ of step 1;
4. compute the PLR statistic for testing hypotheses $H_0 : \text{rank}(\mathbf{\Pi}) \leq r$ vs. $H_1 : \text{rank}(\mathbf{\Pi}) = k$ for each bootstrap sample of step 3.

For $r = 0, 1, \ldots, k-1$, the bootstrap p-value for the PLR test is given by the relative frequency of bootstrapped PLR statistic replications, which are greater than the PLR statistic for the original sample.

As for Johansen's test, the PLR test can also be used to test for a unit root in a scalar time series.

5.2 Harris' principal components based cointegration test

In order to further robustify the results of Lucas' PLR test, we wanted a test having the alternative hypothesis as null and vice versa. Harris's (1997) cointegration test hypotheses are, indeed,

$$H_0 : \text{rank} \leq r \quad \text{vs.} \quad H_1 : \text{rank} > r. \tag{2}$$

The basic idea of Harris (1997) is to estimate the r "most stationary" linear combinations of the k time series, using the last r principal components (PC), and applying a multivariate version of the KPSS test (Nyblom and Mäkeläinen 1983, Kwiatkowski *et al.* 1992) for testing their joint stationarity.

Consider the k-dimensional cointegrated system

$$\begin{aligned} \boldsymbol{\beta} \boldsymbol{y}_t &= \boldsymbol{z}_t \\ \boldsymbol{\beta}'_{\perp} \Delta \boldsymbol{y}_t &= \boldsymbol{w}_t, \end{aligned}$$

where $\boldsymbol{\beta}$ is a full rank $k \times r$ matrix of cointegrating vectors and $\boldsymbol{\beta}_\perp$ is a full rank $k \times (k-p)$ matrix such that $\boldsymbol{\beta}'\boldsymbol{\beta}_\perp = \mathbf{0}$, while $\zeta_t = (\boldsymbol{z}_t', \boldsymbol{w}_t')'$ is a zero-mean stationary process, satisfying the functional central limit theorem.

Since, under the null hypothesis, the smallest r PCs are super-consistent estimates of vectors spanning the cointegration space (Harris 1997, Lemma 1), but their asymptotic distribution depends on nuisance parameters, Harris (1997) proposes a semi-parametric correction to the data, based on these PC estimates.

The nuisance parameters in the asymptotic distribution of the PC estimators are

$$\begin{bmatrix} \boldsymbol{\Omega}_{zz} & \boldsymbol{\Omega}_{zw} \\ \boldsymbol{\Omega}_{wz} & \boldsymbol{\Omega}_{ww} \end{bmatrix} = \sum_{j=-\infty}^{\infty} \mathbb{E}[\boldsymbol{\zeta}_{t-j}\boldsymbol{\zeta}_t']$$

$$\boldsymbol{\Delta}_{wz} = \sum_{j=0}^{\infty} \mathbb{E}[\boldsymbol{w}_{t-j}\boldsymbol{z}_t'].$$

Since the first $k-r$ PCs are super-consistent estimates of $\boldsymbol{\beta}_\perp$, and the last r PCs are super-consistent estimates of $\boldsymbol{\beta}$, the nuisance parameters may be consistently estimated as HAC covariance matrices of the residuals

$$\hat{\boldsymbol{z}}_t = \hat{\boldsymbol{\beta}}'\boldsymbol{y}_t$$

$$\hat{\boldsymbol{w}}_t = \hat{\boldsymbol{\beta}}_\perp'\boldsymbol{y}_t.$$

Now, define

$$\hat{\boldsymbol{\Omega}}_{ab} = \sum_{j=-T+1}^{T-1} \kappa\left(\frac{j}{\gamma_T}\right)\hat{\Gamma}_{ab}(j),$$

$$\hat{\boldsymbol{\Delta}}_{ab} = \sum_{j=0}^{T-1} \kappa\left(\frac{j}{\gamma_T}\right)\hat{\Gamma}_{ab}(j),$$

with

$$\hat{\Gamma}_{ab}(j) = T^{-1}\sum_{t=j+1}^{T} \boldsymbol{a}_{t-j}\boldsymbol{b}_t',$$

$\boldsymbol{a}_t$ and $\boldsymbol{b}_t$ vector time series, $\kappa(\cdot)$ a kernel function and γ_T a bandwidth parameter such that $\gamma_T \to \infty$ and $\gamma_T/T \to 0$ as $T \to \infty$ (Andrews 1991, Newey and West 1994). Harris (1997, Theorem 2) proves that the r smallest PCs of

$$\boldsymbol{y}_t^* = \boldsymbol{y}_t - \hat{\boldsymbol{\beta}}(\hat{\boldsymbol{\beta}}'\hat{\boldsymbol{\beta}})^{-1}\hat{\boldsymbol{\Omega}}_{zw}\hat{\boldsymbol{\Omega}}_{ww}^{-1}\hat{\boldsymbol{w}}_t - \hat{\boldsymbol{\beta}}_\perp(\hat{\boldsymbol{\beta}}_\perp'\hat{\boldsymbol{\beta}}_\perp)^{-1}\hat{\boldsymbol{\Delta}}_{w\zeta}\hat{\boldsymbol{S}}_{\zeta\zeta}^{-1}\hat{\boldsymbol{\zeta}}_t,$$

where $\hat{\boldsymbol{S}}_{\zeta\zeta} = T^{-1}\sum\boldsymbol{\zeta}\boldsymbol{\zeta}'$, are super-consistent estimators of vectors spanning the cointegration space and their asymptotic distribution is free of nuisance parameters. Moreover, these estimators are asymptotically efficient.

Harris (1997, Theorem 3) also finds the asymptotic distribution also under de-meaning and OLS de-trending of the original time series.

The test statistic for testing the hypothesis (2) is

$$T^{-2} \sum_{t=1}^{T} \hat{\boldsymbol{s}}_t' \hat{\boldsymbol{\Omega}}_{zz}^{*-1} \hat{\boldsymbol{s}}_t,$$

with

$$\boldsymbol{s}_t = \sum_{j=1}^{t} \hat{\boldsymbol{z}}_j^*, \qquad \hat{\boldsymbol{z}}_j^* = \hat{\boldsymbol{\beta}}^{*\prime} \boldsymbol{y}_t^*$$

and $\hat{\boldsymbol{\beta}}^*$ matrix, whose columns are the smallest r PCs of $\boldsymbol{y}_t^*$.

The test statistic is computed for $r = k, k-1, \ldots$ until the null hypothesis is rejected. The asymptotic distributions of the statistic are derived by Harris (1997, Theorem 7) for the case of de-meaned and OLS de-trended series and the relevant critical values are tabulated in the same article.

5.3 Robust stationarity testing

In a very recent article, de Jong *et al.* (2007) proposed a robustification of the classic KPSS (Kwiatkowski *et al.* 1992) test for stationarity. Their basic idea is to compute the KPSS statistic on the sign of median centered data. More explicitly, let m_T be the sample median of the observations $\{x_1, \ldots, x_T\}$, $\mathrm{sgn}(x)$ the sign function assuming the values $\{-1, 0, 1\}$ when, respectively, $x < 0$, $x = 0$, $x > 0$, and

$$S_t = \sum_{i}^{t} \mathrm{sgn}(x_i - m_T).$$

The Index KPSS (IKPSS) test statistic for stationarity is given by

$$\mathrm{IKPSS}_T = \hat{\sigma}^{-2} T^{-2} \sum_{t=1}^{T} S_t^2, \tag{3}$$

where $\hat{\sigma}^2$ is a HAC estimator of the long-run variance

$$\hat{\sigma}^2 = T^{-1} \sum_{i=1}^{T} \sum_{j=1}^{T} \kappa\left(\frac{i-j}{\gamma_T}\right) \mathrm{sgn}(x_i - m_T)\,\mathrm{sgn}(x_j - m_T),$$

with kernel function $\kappa(\cdot)$ and bandwidth γ_T (Andrews 1991, Newey and West 1994). de Jong *et al.* (2007) prove that under the null of stationarity (and very weak additional conditions) the IKPSS statistic has the same asymptotic distribution as the KPSS test:

$$\mathrm{IKPSS}_T \Rightarrow \int_0^1 V_1(r)^2 \mathrm{d}r \tag{4}$$

percentile	.90	.95	.99
IKPSS_{250}	.123	.151	.218
IKPSS_{250}(Bartlett)	.122	.150	.214
IKPSS_{1000}	.120	.149	.220
IKPSS_{1000}(Bartlett)	.120	.149	.215
$\int_0^1 V_2(r)^2 \mathrm{d}r$	.119	.146	.216

Table 5: Monte Carlo percentiles based on the IKPSS statistic after LAD-detrending.

where $V_1(r)$ is a standard Brownian bridge and $\Rightarrow$ denotes weak convergence. Monte Carlo simulations prove good size properties of this test, and better power properties than the KPSS under fat tail distributions. Result (4) holds even if moments do not exist.

The IKPSS test may be generalized to test trend stationarity, detrending the series by means of least absolute deviations (LAD) regression and taking the signs of the regression residuals. de Jong *et al.* (2007) point out that the relevant asymptotic theory is much more involved, but few Monte Carlo experiments on linear-trend stationary time series performed by us confirm that, under the null, the IKPSS statistic has the same asymptotic distribution as the KPSS test with OLS detrending, that is, $\int_0^1 V_2(r)^2 \mathrm{d}r$, where $V_2(r)$ is a second level Brownian bridge. Table 5 reports our results of Monte Carlo experiments, where the empirical percentiles of the LAD-detrended IKPSS statistic have been computed on $10,000$ replications using, respectively, the sample variance and HAC estimates based on the Bartlett kernel with bandwidth $\lfloor 4(T/100)^{2/9} \rfloor$. The data generating process was $y_t = 2.653 + 0.003t + 0.25z_t$, with $z_t \sim IN(0,1)$, where the coefficients have been chosen to match those of the LAD regression of the EEX series on a linear trend. The approximation seems to be very good for samples of 250 or more observations: in our analysis, only samples of greater sizes will be considered.

6 A long run analysis of European electricity prices

6.1 Unit roots

The first step of our empirical study consists in a thorough and robust unit roots analysis.

Table 6 reports Lucas PLR tests with relative probability values for all the series with the number of lags of the differenced series ranging from 1 to 8. The number of lags is usually selected by information criteria, but in the presence of additive outliers these may be misleading (Martin 1980). By analyzing the correlogram of the differenced series (Figure 3), with the exception of Nordpool, we notice a very similar linear memory on all series, which could be well approximated by an MA(2) process. This evidence is consistent with our conjecture that the process generating electricity (log-)prices may be a random walk, possibly with drift, superimposed to a very leptokurtic short memory noise:

$$\begin{aligned} y_t &= \mu_t + \eta_t \\ \mu_t &= \delta + \mu_{t-1} + \varepsilon_t, \end{aligned} \tag{5}$$

where ε_t is a white noise and η_t is well approximated by some stable and invertible ARMA process. Taking differences of (5) leads necessarily to a process with an invertible MA component. In fact,

$$\Delta y_t = \delta + \varepsilon_t + \Delta\eta_t$$

is the sum of the non-invertible ARMA process $\Delta\eta_t$ with a non-degenerate white noise, and this sum may be easily proved to be an invertible ARMA(p, q) process, with $q \geq 1$.

Since the PLR statistic is based on the same auxiliary model as the Augmented Dickey-Fuller, we have to approximate an MA(2) process with an AR(p) and, therefore, the tests in Table 6 are reliable only when the number of lags p is large enough[5]. This is confirmed by the stabilization of the test statistics and the relative probability values as the lag order increases. At a 5$\%$ level, the unit root hypothesis cannot be rejected for any time series when the auxiliary equation has 4 or more lagged differences[6].

The stationarity tests in Table 7 confirm the findings of the unit root tests. We provide tests statistics both using Bartlett and Quadratic Spectral kernels with bandwidth computed according to Newey and West (1994, Table II, panel C).

We also applied other non-robust unit root tests commonly found in commercial packages (here not reported), which gave non-univocal outcomes and in many cases rejected the unit root hypothesis in favour of trend stationarity.

6.2 Cointegration

Having established with a good degree of confidence that log electricity prices are unit root processes, the second question we want to consider is the presence of common trends in the price dynamics of the different European markets. This issue is relevant from a least two point of views. On the one hand, it addresses the question about the existence of an integrated European electricity market against the idea that only separated national markets exist. On the other hand, since some European countries have rather developed financial markets of electricity derivatives, while others do not, the presence of cointegration would permit operators in the latter countries to expand their choice of financial instruments for hedging strategies.

[5]Notice that our bootstrap strategy uses independent resampling rather than block resampling, making the p-values reliable only when the dynamic structure of the stationary part of the auxiliary model has been properly taken into account.

[6]We report results only for the longest common sample (March 2002-March 2007), which are not very different from the results obtained using the whole individual samples.

lags	APX	prob.	EEX	prob.	EXAA	prob.	POWER	prob.	OMEL	prob.	NORD	prob.
Constant												
1	6.063	0.016	6.710	0.010	7.775	0.007	9.875	0.002	6.587	0.016	2.290	0.161
2	5.197	0.028	4.895	0.028	6.064	0.022	8.149	0.005	4.047	0.059	2.461	0.148
3	4.453	0.040	4.244	0.045	4.708	0.043	5.586	0.022	3.240	0.095	1.924	0.206
4	3.292	0.077	2.513	0.125	3.328	0.085	3.133	0.089	2.594	0.142	3.645	0.082
5	2.799	0.097	2.026	0.174	2.919	0.107	2.460	0.127	2.486	0.154	4.712	0.053
6	3.629	0.064	2.572	0.118	3.691	0.072	2.879	0.107	1.882	0.218	5.508	0.037
7	3.118	0.087	2.486	0.129	2.874	0.108	2.028	0.170	2.010	0.203	5.005	0.045
8	3.386	0.079	2.598	0.130	2.927	0.099	1.614	0.225	1.853	0.223	6.170	0.028
Linear trend												
1	10.191	0.009	14.061	0.001	14.903	0.001	19.249	0.000	6.800	0.236	0.426	0.926
2	8.854	0.021	11.678	0.004	11.382	0.007	15.503	0.001	4.250	0.511	0.641	0.902
3	7.179	0.060	10.663	0.007	9.427	0.019	11.710	0.005	3.256	0.648	0.364	0.936
4	4.508	0.209	5.767	0.093	4.808	0.178	7.072	0.046	2.433	0.761	1.496	0.825
5	2.276	0.540	3.383	0.307	3.335	0.332	4.811	0.149	2.456	0.736	2.129	0.756
6	3.131	0.387	4.084	0.235	3.888	0.284	4.305	0.196	1.692	0.831	2.515	0.710
7	3.326	0.302	3.680	0.295	2.641	0.452	3.546	0.252	1.829	0.805	2.309	0.743
8	2.475	0.461	2.729	0.460	1.714	0.660	1.814	0.574	1.490	0.866	3.698	0.599

Bootstrap p-values based on 10,000 repetitions.

Franses and Lucas's (1998, Table 1) "conservative" .90, .95 and .99 quantiles are 7.0, 8.7 and 12.5 (constant) and 3.0, 4.3 and 7.0 (trend).

Tests based on the common longest sample ranging from 25/02/02 to 12/03/07.

Table 6: Unit root tests based on Lucas PLR ratios.

	APX	EEX	EXAA	POWER	OMEL	NORD
Constant						
$KPSS_{\text{Bartlett}}$	3.082	3.129	3.169	3.340	1.258	0.889
$KPSS_{\text{Quadratic}}$	3.022	3.147	3.199	3.263	1.360	0.866
$IKPSS_{\text{Bartlett}}$	3.743	3.657	3.526	4.358	1.277	0.658
$IKPSS_{\text{Quadratic}}$	2.892	2.842	2.736	3.339	0.991	0.505
Linear trend						
$KPSS_{\text{Bartlett}}$	0.156	0.176	0.150	0.214	0.292	0.199
$KPSS_{\text{Quadratic}}$	0.190	0.228	0.198	0.263	0.337	0.204
$IKPSS_{\text{Bartlett}}$	0.191	0.172	0.189	0.262	0.412	0.349
$IKPSS_{\text{Quadratic}}$	0.154	0.141	0.155	0.215	0.320	0.267

.90, .95 and .99 percentiles: .347, .463 and .793 (constant), .119, .146 and .216 (trend).
Bandwidth: $\lfloor 4(T/100)^{2/9} \rfloor$ (Bartlett kernel), $4(T/100)^{2/25}$ (quadratic spectral kernel).

Table 7: Stationarity tests.

We started testing for cointegration among the four central European markets APX, EEX, EXAA and Powernext, since their networks are well connected and Figure 2 suggests the presence of common features. Then, we added the remaining markets in our sample (OMEL and NordPool).

According to Table 8, APX, EEX, EXAA and Powernext share a common trend, while OMEL and NordPool do not. Cointegration rank tests have been computed leaving only a restricted constant as deterministic variable, since we want to test for the presence of common trends, and not for the common stochastic part of different trends only.

Robust estimates of the cointegration vectors for the APX, EEX, EXAA and Powernext are reported in Table 9. The three free parameters (third line of the cointegration matrix) are not very far from the value -1. If the true cointegration matrix were

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ -1 & -1 & -1 \end{bmatrix}$$

we would have the relationship between markets that DeVany and Walls (1999b) call *Strong markets integration*. If two or more markets are strongly integrated they have the same long-run rate of growth. Table 9 reports PLR tests for strong integration restrictions, and relative bootstrap p-values. The strong integration hypothesis is not supported by the data. In order to assess whether single pairs of time series are strongly integrated, we applied the IKPSS test to the series

$$y_t^{(i)} - y_t^{(j)}, \qquad i = 1, \ldots, 4, \;\; j = i + 1, \ldots, 4,$$

obtaining the results reported in Table 10. EEX and Powernext appear to be the only pair of strongly integrated markets.

We also applied Harris' cointegration rank test, but, while the results for the system APX, EEX, EXAA and Powernext are rather stable across different choices

	0 lags		1 lag		2 lags		3 lags	
rank $\leq$	PLR	prob.	PLR	prob.	PLR	prob.	PLR	prob.
			APX, EEX, EXAA, Powernext					
0	389.5	0.000	247.1	0.000	206.3	0.000	169.1	0.000
1	223.2	0.000	142.8	0.000	130.7	0.000	93.2	0.000
2	101.3	0.000	64.8	0.000	51.0	0.000	35.6	0.002
3	6.6	0.225	3.4	0.492	1.9	0.756	2.0	0.676
			APX, EEX, EXAA, Powernext, OMEL					
0	411.2	0.000	260.7	0.000	224.1	0.000	181.6	0.000
1	242.6	0.000	156.3	0.000	131.4	0.000	96.4	0.000
2	116.2	0.000	72.3	0.000	58.8	0.001	39.7	0.048
3	14.9	0.332	8.5	0.762	5.4	0.938	5.3	0.936
4	6.3	0.257	1.7	0.750	1.2	0.841	2.1	0.662
			APX, EEX, EXAA, Powernext, NordPool					
0	408.9	0.000	272.5	0.000	223.2	0.000	190.7	0.000
1	250.3	0.000	168.8	0.000	146.6	0.000	120.7	0.000
2	128.4	0.000	86.4	0.000	78.2	0.000	44.7	0.016
3	13.6	0.285	10.4	0.527	8.2	0.718	7.3	0.817
4	3.5	0.375	3.9	0.366	2.5	0.664	1.9	0.679

Deterministic variables: restricted constant.
Bootstrap p-values based on 10,000 replication.

Table 8: PLR cointegration rank tests.

	1 lagged difference			3 lagged differences			Harris estimates		
	$\boldsymbol{\beta}_1$	$\boldsymbol{\beta}_2$	$\boldsymbol{\beta}_3$	$\boldsymbol{\beta}_1$	$\boldsymbol{\beta}_2$	$\boldsymbol{\beta}_3$	$\boldsymbol{\beta}_1$	$\boldsymbol{\beta}_2$	$\boldsymbol{\beta}_3$
APX	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00
EEX	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00
EXAA	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
POWER	-1.03	-0.96	-0.94	-1.02	-0.95	-0.93	-1.01	-0.95	-0.94
Const.	0.02	-0.17	-0.27	-0.02	-0.23	-0.32	-	-	-
PLR		13.098			10.919				
prob.		0.002			0.012				

p-values based on 10,000 bootstrap sample points.

Table 9: Estimated cointegration vectors and strong integration test.

	APX	EEX	EXAA	POWER
APX	-	0.615	0.982	0.551
EEX	-	-	0.629	*0.328*
EXAA	-	-	-	0.843
POWER	-	-	-	-

Asympt. .90, .95, .99 percentiles: 0.347, 0.463, 0.739.
Bartlett kernel with bandwidth $\lfloor 4(T/100)^{2/5} \rfloor$.

Table 10: IKPSS tests for strong integration between pairs of price series.

of kernel functions and bandwidth parameters, when OMEL and NordPool are added, results become very sensible to these side-conditions.

rank $\leq$	Test Stat.	10%	5%	1%
APX, EEX, EXAA, POWER				
4	11071.	1.06	1.23	1.60
3	0.45667	0.59	0.72	1.06
2	0.28262	0.30	0.37	0.60
1	0.28482	0.12	0.16	0.28
APX, EEX, EXAA, Power, OMEL, Nord				
6	9455.6	1.48	1.69	2.13
5	0.65830	0.93	1.09	1.46
4	0.99480	0.55	0.67	0.95
3	0.50951	0.31	0.38	0.57
2	0.42730	0.17	0.21	0.32
1	0.29461	0.076	0.097	0.15

Quadratic Spectral kernel with bandwidth selected by Andrews's (1991) AR(1)-based method.

Table 11: Harris cointegration rank test.

The (normalized) cointegration vectors estimates obtained by Harris' method are very similar to those obtained by Lucas' (Table 9).

The joint application of the above tests suggests that APX, EEX, EXAA and Powenext are cointegrated, with strong integration holding only approximatively[7]. Omel and NordPool do not seem to share a common trend with the other markets. Notice, however, that Harris' test, not being outlier-robust, tends to be biased towards stationarity and suggests too many cointegrating relations. By visual inspection of the cointegrating relations estimated by Harris' method applied to the six time series (not reported), we are quite confident in excluding cointegration with NordPool, while more doubts rise when Omel is considered.

In order to study the relationship among the four markets that appear to be more integrated, i.e. APX, EEX, EXAA and Powernext, we fitted the multivariate unobserved components model (UCM)

$$\begin{aligned}\boldsymbol{y}_t &= \boldsymbol{\mu}_t + \boldsymbol{\chi}_t + \boldsymbol{\varepsilon}_t\\ \boldsymbol{\mu}_t &= \boldsymbol{\mu}_{t-1} + \boldsymbol{\delta} + \boldsymbol{\eta}_t\\ \boldsymbol{\chi}_t &= \boldsymbol{\Phi}\boldsymbol{\chi}_{t-1} + \boldsymbol{\zeta}_t,\end{aligned}$$

where $\boldsymbol{\varepsilon}_t$, $\boldsymbol{\eta}_t$ and $\boldsymbol{\zeta}_t$ are white noise processes with variances Σ_ε, Σ_η and Σ_ζ (cf. Harvey 1989). We estimated the model using standard linear Kalman filtering and quasi-Gaussian maximum likelihood methods. We conjectured that the normality assumption should not harm much the estimates relative to the low frequency

[7]The hypothesis is not supported by the data, but the difference between the hypothesized values and the estimates is probably negligible in practical applications.

components $\boldsymbol{\mu}_t$, being the leptokurtic noise absorbed mostly by the other two components.

The estimated[8] covariance/correlation matrix of the shocks $\boldsymbol{\eta}_t$ of the random walk components is

$$\frac{1}{100}\begin{bmatrix} 0.22 & 100.00 & 100.00 & 100.00 \\ 0.20 & 0.18 & 100.00 & 100.00 \\ 0.18 & 0.17 & 0.15 & 100.00 \\ 0.20 & 0.19 & 0.17 & 0.19 \end{bmatrix},$$

where the upper triangular part contains correlations. These estimates strongly suggest the presence of a single trend that drives the four time series. As for the slope coefficients $\boldsymbol{\delta}$, the estimates are very similar and the hypothesis of a common slope cannot be rejected:

$$\boldsymbol{\delta}' = \begin{bmatrix} \underset{(.0030)}{.0017} & \underset{(.0028)}{.0018} & \underset{(.0026)}{.0019} & \underset{(.0028)}{.0020} \end{bmatrix},$$

(standard error in parenthesis). This finding validates our choice about the deterministic component (restricted constant) in Lucas' cointegration tests: the *whole* trend is common, not only the stochastic part.

Notice that if only one trend drives the four time series, then the UCM model above may be rewritten

$$\begin{aligned} \boldsymbol{y}_t &= \boldsymbol{w}\mu_t + \boldsymbol{\mu}_0 + \boldsymbol{\delta}t + \boldsymbol{\chi}_t + \boldsymbol{\varepsilon}_t \\ \mu_t &= \mu_{t-1} + \eta_t \\ \boldsymbol{\chi}_t &= \boldsymbol{\Phi}\boldsymbol{\chi}_{t-1} + \boldsymbol{\zeta}_t, \end{aligned}$$

with μ_t scalar random walk process and $\boldsymbol{w}$ vector of loadings. The null space of the estimates $\hat{\boldsymbol{w}} = (1.00, 0.91, 0.84, 0.93)'$ is an estimate for the cointegration space, and is spanned by the columns of the matrix

$$\begin{bmatrix} 1.00 & 0.00 & 0.00 \\ 0.00 & 1.00 & 0.00 \\ 0.00 & 0.00 & 1.00 \\ -1.08 & -0.98 & -0.90 \end{bmatrix},$$

which may be compared to those in Table 9.

If the same UCM is estimated using data of APX, EEX, EXAA, Powernext and OMEL, the correlations of the trend disturbances among the first four series are still very close to one (above .99), but the correlations with OMEL are smaller than 0.80. If OMEL is substituted for NordPool, the relevant correlations are even lower (around 0.60).

[8] We used the package STAMP 6.2 by S.J. Koopman and A.C. Harvey.

6.3 Long run relations among electricity prices, gas prices and oil prices

As was shown in Section 2, a significant part of the electricity produced in Europe is generated using natural gas and oil. Moreover, we recall that all the wholesale electricity markets considered in the paper work under the SMP rule. This implies that the marginal generating unit sets the closing price for electricity for each hour of the next day. Consequently, each SMP crucially depends upon the technological/cost characteristics of the marginal plant (see section 2. For example, in 83% of the hours of each week, the SMP is fixed by thermal plants in the Powernext's market (82% is the median value), and in 67% of the hours (70% median value) in the EEX market. On the contrary, the corresponding values for Omel are 47% (mean) and 46% (median). These differences accord with the previous results that the Omel market appears to be less correlated with the central European markets.

In the light of the above considerations, it is interesting at this stage to assess the long run relations among electricity prices, gas prices, and oil prices. For natural ga,s we used weekly medians of the Zeebrugge midday price index (ZEEBDAHD Index), as the Zeebrugge Hub is the most liquid natural gas market in continental Europe. As for oil, we used the Brent priced in Euro.

Figure 4 depicts an integrated linear combination[9] of APX, EEX, EXAAA and Powernext prices together with the Zeebdahd Index and Brent prices (common scale and mean).

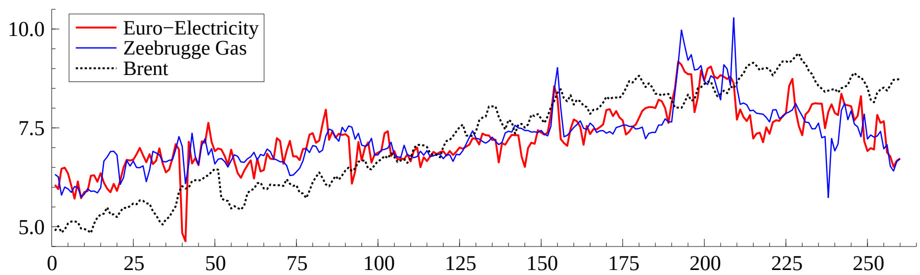

Figure 4: Electricity, natural gas and oil prices on a common scale.

There is strong evidence of a common long-term dynamics between electricity prices and gas prices. Oil prices have experienced a faster growth. The long-run relation between oil and electricity prices seems possible only on the stochastic part of the trends.

We applied Lucas' test to APX, EEX, EXAA, Powernext and Zeebrugge. We tested for the cointegration rank using both restricted and unrestricted constants and letting 0 through 8 lags of the differenced dependent variable (only results up

[9] We used a vector spanning the null space of the cointegration matrix of Table 9 (center), estimated using the VECM(3) with Student's t_5 innovations and cointegration rank equal to 3.

to 3 lags are reported in Table 12). All the tests selected 4 cointegrating relations. The result is also confirmed by Harris' test (not reported).

	0 lags		1 lag		2 lags		3 lags	
rank $\leq$	PLR	prob.	PLR	prob.	PLR	prob.	PLR	prob.
APX, EEX, EXAA, Powernext, Zeebrugge / restricted constant								
0	468.350	0.000	281.200	0.000	251.550	0.000	223.710	0.000
1	310.460	0.000	181.820	0.000	168.380	0.000	140.960	0.000
2	177.570	0.000	98.161	0.000	94.634	0.000	78.533	0.000
3	75.816	0.000	40.338	0.000	42.846	0.000	42.262	0.000
4	6.166	0.177	5.359	0.240	2.757	0.550	2.902	0.525
APX, EEX, EXAA, Powernext, Brent / restricted constant								
0	430.980	0.000	289.210	0.000	238.290	0.000	189.860	0.000
1	260.570	0.000	180.260	0.000	161.540	0.000	112.020	0.000
2	134.050	0.000	97.581	0.000	78.792	0.000	56.731	0.001
3	33.628	0.005	23.888	0.046	18.545	0.167	17.241	0.213
4	12.732	0.042	7.622	0.180	7.136	0.196	4.475	0.398
APX, EEX, EXAA, Powernext, Brent / unrestricted constant								
0	422.710	0.000	281.560	0.000	231.430	0.000	184.140	0.000
1	251.980	0.000	172.470	0.000	154.210	0.000	109.940	0.000
2	125.030	0.000	92.578	0.000	74.722	0.000	54.289	0.000
3	24.505	0.012	19.125	0.045	14.361	0.140	14.706	0.139
4	3.304	0.114	2.648	0.159	2.782	0.142	1.837	0.220

Bootstrap p-values based on 10,000 replication.

Table 12: PLR cointegration rank tests.

The normalized cointegration matrix for this system is

$$\begin{bmatrix} 1.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 1.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 1.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 1.00 \\ -2.15 & -2.00 & -1.97 & -2.13 \end{bmatrix},$$

which leaves no doubts about the absence of strong integration of gas prices with any of the electricity markets prices.

Similarly, we applied Lucas' test on APX, EEX, EXAA, Powernext and Brent (in Euro), and the results are reported in the second and third panel of Table 12. The tests have also been conducted assuming an unrestricted constant into the VECM, because from Figure 4 one can notice that the rate of growth[10] of oil prices seems higher than that of electricity prices. If enough lagged differences of the five series are put in the model, oil prices do not seem cointegrated with electricity prices.

[10]Remember that we are modelling log-prices and a drift in the log-metric is a rate of growth in the original data.

7 Concluding comments

This paper analyses the interdependency existing in the dynamics of electricity prices formed in six major European markets (Germany, France, Austria, Netherlands, Spain, and Nordic countries). We conducted a multivariate dynamic analysis of weekly median prices and our results can be summarized as follows. As for unit roots, we obtained that all the series have one unit root. As for cointegration, we obtained that APX, EEX, EXAA, and Powernext share a common trend. They are integrated "nearly" strongly, but the hypothesis of strong integration cannot be rejected only for EEX and Powernext. Omel and Nord Pool do not share a common trend with the other markets, and this accords with the differences existing in the cost/technology characteristics of the electricity generation industries in these countries. For these markets, despite significant differences in the mix of generation technologies, still the generators determining the SMP frequently use gas and oil sources (see 6.3).

As for the relationship between electricity prices and gas prices, we found strong evidence of a common long-term dynamics among them. The same result cannot be reported for oil prices. Altogether, our finding indicates that the European electricity market as a whole is far from being a common market. The French and the German markets seem to form a sort of core zone since they are strongly integrated. The near periphery of this core zone is composed by the Netherlands and Austria, which are cointegrated, but not strongly integrated, with them. It would not be correct to consider Omel and Nord Pool as a far periphery. They have specific characteristics that prevent, probably also in the near future, a complete integration into the European market. Finally, we stress that the existence of a common long term dynamics among electricity prices, and between electricity prices and gas prices may prove to be important for long term hedging operations to be conducted even in markets where there are no electricity derivatives.

References

Andrews, D.W.K. (1991). Heteroscedasticity and autocorrelation consistent covariance matrix estimation. *Econometrica 59*, 817-858.

Armostrong, M. and A. Galli (2005). Are day-ahead prices for electricity converging in continental Europe? An exploratory data approach. Working Paper CERNA, February.

Arranz, M.A. and A. Escribano (2004). Outliers-robust ECM cointegration tests based on the trend components. *Spanish Economic Review 6*, 243-266.

Atkins, F.J. and J. Chen (2002). Some statistical properties of deregulated electricity prices in Alberta. University of Calgary, Department of economics, Discussion paper 2002-06.

Bahnot, K. (2000). Behavior of power prices: implications for the valuation and hedging of financial contracts. *Journal of Risk 2(3).*

Boisselau, F. (2004). *The role of power exchanges for the creation of a single European electricity market: market design and market regulation*. Delft: Delft University Press.

Bosco, B., L. Parisio and M. Pelagatti (2006). Deregulated Wholesale Electricity Prices in Italy. An empirical analysis, *International Advances in Economic Research*, (forthcoming).

Boswijk, P.H. (2000). Testing for a Unit Root with Near-Integrated Volatility. Working paper, Department of Quantitative Economics, Universiteit van Amsterdam.

Bower, J. (2002). Seeking the single European electricity market: evidence from an empirical analysis of wholesale market prices. Working Paper Archive at WUSTL.

Byström, H.N.E. (2005), Extreme value theory and extremely large electricity price changes. *International Review of Economics and Finance 14*, 41-55.

Breitung J. (2002), Nonparametric tests for unit roots and cointegration, *Journal of Econometrics 108*, 343-363.

de Jong, C. and R. Huisman (2002). Option Formulas for Mean-Reverting Power Prices with Spikes. Working paper, Rotterdam School of Management, Erasmus University.

de Jong, R.M., C. Amsler and P. Schmidt (2007). A robust version of the KPSS test based on indicators. *Journal of Econometrics 127*, 311-333.

DeVany, A.S. and W.D. Walls (1999a). Price dynamics in a network of decentralized power markets. *Journal of Regulatory Economics 15*, 123-140

DeVany, A.S. and W.D. Walls (1999b). Cointegration analysis of spot electricity prices: insights on transmission efficiency in the western U.S.. *Energy Economics 21*, 417-434

Deidersen, J. and S. Trück (2002). Energy price dynamics – Quantitative studies and stochastic processes. Technical Document TR-ISWM-12/2002, University of Karlsruhe.

Doornik, J.A. and H. Hansen (1994). A practical test for univariate and multivariate normality. Discussion paper, Nuffield College, Oxford.

Escribano, A., J.I. Peña and P. Villaplana (2002). Modeling electricity prices: international evidence. Universidad Carlos III de Madrid Working Paper 02/07, Economic Series 08, June 2002.

Fabra, N. and J. Toro (2005). Price wars and collusion in the Spanish electricity market, *International Journal of Industrial Organization 23*, 155-181.

Franses, P.H. and N. Haldrup (1994). The effects of additive outliers on tests for unit roots and cointegration, *Journal of Business and Economic Statistics 12*, 471-478.

Franses, P.H. and A. Lucas (1998). Outlier detection in cointegration analysis. *Journal of Business and Economic Statistics 16*, 459-468.

Haldrup, N. and M.Ø. Nielsen (2006). A regime switching long memory model for electricity prices. *Journal of Econometrics 135*, 349376.

Hampel, F.R., E.M. Ronchetti, P.J. Rousseeuw and W.A. Stahel (1986), *Robust Statistics. The Approach Based on Influence Functions*. New York: John Wiley & Sons.

Harris, D. (1997). Principal component analysis of cointegrated time series, *Econometric Theory 13*, 529-557.

Harvey A.C. (1989). *Forecasting, structural time series models and the Kalman filter*, Cambridge: Cambridge University Press.

Huber, P.J. (1981), *Robust Statistics*. New York: John Wiley & Sons.

Huisman, R. and R. Mahieu (2003), Regime jumps in electricity prices, *Energy Economics 25*, 425-434.

Koopman, S.J., M. Ooms and M.A. Carnero (2007). Periodic seasonal Reg-ARFIMA-GARCH models for daily electricity spot prices. *Journal of the American Statistical Association 107*, 16-27.

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

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

Jerko, C.A., J.W. Mjelde and D.A. Bessler (2004). Identifying Dynamic Interactions in Western US Spot Merkets. In D.W. Bumm (Ed.) *Modelling Prices in Competitive Electricity Markets*, New York: John Wiley & Sons.

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

Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. *Econometrica 59*, 1551-1580.

Lange, K.L., J.A. Little and J.M.G. Taylor (1989). Robust Statistical Modeling Using the t distribution. *Journal of the American Statistical Association 84*, 881-896.

Little, R.J.A. (1988). Robust estimation of the mean and covariance matrix from data with missing values. *Applied Statistics 37*, 23-38.

Lucas, A. (1995a). An outlier robust unit root test with an application to the extended Nelson-Plosser data. *Journal of Econometrics 66*, 153-174.

Lucas, A. (1995b). Unit root test based on M-estimators. *Econometric Theory 11*, 331-346.

Lucas, A. (1997). Cointegration testing using pseudolikelihood ratio tests. *Econometric Theory 13*, 149-169.

Lucas, A. (1998a). Inference on cointegrating ranks using LR and LM tests based on pseudo-likelihoods. *Econometric Reviews 17*, 185-214.

Lucia, J.J. and E.S. Schwartz (2002). Electricity prices and power derivatives: evidence from the nordic power exchange. *Review of Derivatives Research 5*, 5-50.

Maronna, R.A., R.D. Martin and V.J. Yohai (2006). *Robust Statistics. Theory and Methods*. Chichester: John Wiley & Sons.

Martin, R.D. (1980) Robust estimation of autoregressive models (with discussion). In *Directions in Time Series*, eds. D.R. Brillinger and G.C. Tiao. Haywood, CA: Institute of Mathematical Statistics, 228-254.

Mount, T.D., Y. Ning and X. Cai (2006). Predicting price spikes in electricity markets using a regime-switching model with time varying parameters. *Energy Economics 28*, 62-80.

Newey, W.K. and K.D. West (1994). Automatic lag selection in covariance matrix estimation. *Review of Economic Studies 61*, 631-654.

Nyblom, J. and T. Mäkeläinen (1983). Comparison of tests for the presence of random walk coefficients in a simple linear model. *Journal of the American Statistical Association 78*, 856-864.

Park, H., J.W. Mjelde and D.A. Bessler (2006). Price dynamics among U.S. electricity spot markets. *Energy Economics 28*, 81-101.

Phillips, P.C.B. and P. Perron (1988). Testing for a unit root in time series regression. *Biometrika 75*, 335-346.

Snell, A. (1999). Testing for r versus $r-1$ cointegrating vectors. *Journal of Econometrics 88*, 151-191.

Stock, J.H. and M. Watson (1998). Testing for common trends. *Journal of the American Statistical Association 83*, 1097-1107.

Swensen, A.R. (2006). Bootstrap algorithms for testing and determining the cointegration rank in VAR models. *Econometrica 74*, 16991714.

Tatsuoka, K.S. and D.E. Tyler (2000). On the uniqueness of S-functionals and M-functionals under nonelliptical distributions. *The Annals of Statistics 28*, 1219-1243.

Villar, J.A. and F.L. Joutz (2006). The relationship between crude oil and natural gas prices. Report of the Energy Information Administration, Office of Oil and Gas.

Wilkinson, L. and J. Winsen (2002). What can we learn from a statistical analysis of electricity prices in New South Wales. *The Electricity Journal*, April, p. 60-69.

Worthington, A.C. and H. Higgs (2004). Transmission of Prices and Volatility in the Australian Electricity Spot Markets. In D.W. Bumm (Ed.) *Modelling Prices in Competitive Electricity Markets*. New York: John Wiley & Sons.

Zachmann, G. (2005). Convergence of Electricity Wholesale Prices in Europe? A Kalman Filter Approach. DIW Discussion Paper 512, Technische Universität Dresden.