Multiscale Analysis of European Electricity Markets

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Abstract

Electricity is considered a new commodity, mainly since the start of the electricity markets liberalization. However it represents an increasingly important sector of trading and as such a challenging area of research. Here we focus on the role of electricity power exchanges for the creation of a single European electricity market, on a different empirical perspective. We use daily power exchange prices of 6 European electricity markets resorting to a novel econometric technique to study correlation at different time scales, known as wavelet analysis, through coherence and phase analysis.

Results give limited support to the assumption of a single "European electricity market", especially at lower scales (high frequency data). Although some European countries share a common trend, the hypothesis of strong integration holds only for some geographically closer countries, but not the perfect integration among the markets considered in the sample. We also find that despite the year 2005, coherence among the series has been high, whereas we also try to infer some possible causes for this lack of perfect integration in the current days.

Keywords – Electricity Prices; Continuous Wavelet Transform; Wavelet Coherency; Wavelet phase; Comovements; European Regulation

EFM classification codes: 350; 630

1. Introduction

In Europe, the reorganization of the electricity industry has been driven by the first and the second Electricity Directives of 1996 and 2003, respectively, and more recently enhanced by the 2007 energy package. They have been followed by a series of recommendations (such as new cross-border lines and a common regulation of cross-border trade) to lead the creation of a truly common European electricity market. The main objective of this EU legislation has been to reduce barriers to trade and to compel Member States to liberalize their electricity industries, thereby increasing efficiency and reducing prices.

While the newly created national wholesale markets show several important institutional similarities (same market design and homogeneous 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.

In this work we address the question of whether the similarities in the electricity market mechanism across European countries are able to lead the dynamics of equilibrium electricity prices. Since price data show peculiar characteristics (leptokurtosis, outliers, periodicity of various kinds, etc.), for this analysis we have used a recently new technique to decompose the daily time series in the time-scale domain.

It is important to search for common trends at different time scales since it may support the view that the European electricity markets are well integrated; for the design of cross-border hedging strategies; and due to different horizon investment decisions. In contrast to methods employed in previous studies (cointegration tests), wavelets allow us to decompose a time series into different time scales (time horizons). Due to the different decision-making time scales among traders, the true dynamic structure of the relationship among spot prices across different European countries itself will vary over the different time scales associated with those different horizons. If integrated dynamics of electricity prices is found this indicates that markets are evolving consistently with European Commission projects. On the other hand, if poor or no integration is evident, this would suggest that national structural differences are still dominant and that they affect price behavior more heavily than the common regulation framework desired. Yet, an analysis of this kind is important in order to evaluate the state of the integration process of the European markets.

What are then these special characteristics? Electricity is not efficiently directly storable, and as such prices are very volatile, where seasonal and price spikes frequently occur. In fact, the design of electricity markets is complex due to a series of electricity characteristics that affect supply and demand. These physical characteristics complicate the design of electricity markets. Electricity has to be consumed within a tenth of a second after its production by virtually all consumers. The supply and demand of power must be kept in a near continuous balance throughout the entire grid to avoid frequency and voltage fluctuations, which can damage generation and transmission equipment. Extreme volatility, mean-reversion, skewness and kurtosis of returns, jumps and spikes, and the seasonal (daily, weekly, annual) behavior of electricity prices (due to cooling and heating needs), differentiate the power market from all other commodity markets (Huisman, Huurman and Mahieu, 2007).

Economists have attempted to explain and forecast the movements of electricity prices in Europe and other continental markets. Most of these analysis techniques are based on the quantitative approach that is often implemented with the classical data analysis technique that is ideal for stationary signals (time invariant). However, the real data for electricity prices, due to its special characteristics is not necessarily stationary.

Since the conventional statistical methods have proven to be inadequate to describe the evolutionary nature of most of the real-world time series data, the research community has provided us an alternative perspective of looking into the data by using the signal processing approach. The present paper uses wavelet transformation to study co-movement of European spot electricity markets that are highly non-linear and non-stationary dynamic processes. The joint time-frequency nature of the wavelet analysis helps to separate the underlying trends found in the spot data for identification of local patterns at various time scales.

The process which followed the EU Directives should enhance the degree of comovements among national European electricity markets. Such an effect is expected to raise electricity markets comovements across countries. Most of the empirical studies investigating the interdependence between European electricity markets have been based on the estimation of a correlation matrix of electricity prices and/or on multivariate analysis techniques, such as cointegration theory and principal component analysis. These techniques, particularly cointegration analysis, analyze the interactions between electricity markets by examining either their short-run or long run relationships as the time series methodologies employed may separate out just two time scales in economic time series. The nature of the relationship between electricity prices may well vary across time scales. Where both the time horizons of decisions and the strength and direction of relationships between market prices may differ according to the time scale of the analysis a useful analytical tool may be represented by wavelet analysis.

Some authors have concentrated on the fuel market side. Siliverstovs et al. (2005) investigate the degree of integration of natural gas markets in Europe, North America and Japan through principal component analysis. De Vany and Walls (1993) use cointegration analysis in locational spot natural gas markets. Panagiotidis and Rutledge (2007) found no evidence to show that oil and gas prices "decoupled" after liberalization. Bencivenga and Sargenti (2009) investigate the short and long run relationship between crude oil, natural gas and electricity prices in US and in European commodity markets. They use daily price data over the period 2001-1009 and perform a correlation analysis to study the short term relationship, while the long run relationship is analyzed using the Engle-Granger cointegration framework through the Error Correction Model. Results show an erratic relationship in the short term while in the long term an equilibrium relationship may be found.

Resorting to electricity markets, Woo, Lloyd-Zanetti and Horowitz (1997) use cointegration techniques to study locational spot electricity markets. De Vany and Walls (1999) estimate a vector error correction model for electricity spot prices in 11 regional markets in the western United States. Results show evidence of an efficient and stable wholesale power market. The studies of Bower (2002), Boisseleau (2004) and Armstrong and Galli (2005) compare electricity day ahead wholesale prices at various power exchanges in Europe. Bower (2002) applies correlation and cointegration analysis to prices from the Nordic Countries, Germany, Spain, England and Wales as well as the Netherlands in 2001. He concludes that some integration of European markets was already present in 2001, especially between the Netherlands and its neighbors and within the Nord Pool area. However, his use of unweighted daily averaged data is a flaw given the strong differences of peak and off-peak price behavior on the electricity market. Boisseleau (2004) focuses on regression and correlation analysis determining that the level of integration of European markets is quite low. Both Bower (2002) and Boisseleau (2004) describe the respective status quo of electricity market integration. Armstrong and Galli (2005) analyze the European price developments over time. They study the evolution of price differentials between France, Germany, the Netherlands and Spain in the years 2002 to 2004 (Bosco et al., 2009, points out some critics to their study). Turvey (2006) examined the use of interconnectors and the pricing of scarce transmission capacities. Based on the example of the Anglo-French Interconnector, he provided empirical evidence for the insufficient correlation of flows and price differentials.

Zachmann (2008) based on a Principal Component Analysis of wholesale electricity prices in Austria, Germany, Netherlands, Denmark, Sweden, Poland, Czech Republic, UK, Spain and France between 2002 and 2006 reject the assumption of full market integration. He uses hourly data to examine intraday developments and compare them across markets. More recently, Bosco et al. (2009) results of a robust multivariate long-run dynamic analysis reveal the presence of four highly integrated central European markets (France, Germany, the Netherlands and Austria), not for Spain and the Nordic market. In order to explore the long run dynamics and common features of time series they rely on median filtering, robust parametric tests with unit roots or less cointegration under the null hypothesis and robust semi-parametric tests with mean reversion or more cointegration under the null. Their results point out for no overall integration of electricity European markets. On a different perspective, Robinson (2008) considers the impact of EU directives on the evolution of electricity prices using beta-convergence and cointegration. Although mixed, results suggest that convergence did not occur for Denmark, Finland, France, Germany, Greece, Ireland, Italy, Portugal, Spain and the UK from 1978 to 2003. However, they use electricity prices for households and industry quoted in US dollars per kilowatt hour. As such, retail price rather than wholesale prices are used, being the retail price the wholesale price plus a supply and transmission element.

Previous research findings indicate that the European electricity market as a whole is far from being a true common market, and we explore here this hypothesis resorting to wavelet analysis. As opposed to the previous literature, this work employs wavelets in detecting relationships among the variables. Wavelet transform is a multi-scale analysis method to detect the signal in different scales. Wavelet analysis performs the estimation of the spectral characteristics of a time series as a function of time revealing how the different periodic components of the time series change over time. They can thus help us to interpret multi-frequency, non-stationary time series data, revealing features we could not see otherwise. Analysis in the frequency domain does not bring additional information, but it is an alternative method to analyze the data. A measure of correlations in the time domain is the coherence in the frequency domain. That's why we use wavelets as a distinct feature from previous works by analyzing European electricity markets comovements through time and scales by means of the Morlet wavelet.

Results point out that although some European countries share a common trend, the hypothesis of strong integration holds only for some geographically closer countries, but not the perfect integration among the markets considered in the sample (especially at higher frequencies). However, the existence of a common long term dynamics among electricity spot prices may prove to be important for hedging. Also, they have specific characteristics that prevent, probably also in the near future, a complete integration into the direction of a single European market.

The paper develops as follows. Section 2 presents the research method to be employed in the empirical part of the work, and section 3 presents the data and descriptive statistics. In section 4 we present the empirical results and discussions. Section 5 concludes the work.

2. Research method: Wavelets

Wavelets are relatively new signal processing techniques/tools in economics and finance, taking their roots from filtering methods[2] and Fourier analysis (Percival and Mofjeld, 1997; Percival and Walden, 2000; and Gençay, Selçuk and Witcher, 2002). However, they overcome most of the limitations of these two methods. Their main advantages are the fact that they combine information from both time-frequency domain, being very flexible, and with wavelets we do not need to make strong assumptions concerning the data generating process for the series under investigation.

What makes wavelets interesting and useful is the fact that its window can be continuously resized. By looking at a signal with a small window only fine features can be viewed whereas by looking at the same signal with a large window the coarse features will be viewed. Thus, by using wavelets we could see both fine details and approximations. The temporal analysis by wavelets is performed with a contracted, high-frequency version of the wavelet, while

[2] Filters allow to capture specific components (trends, cycles, seasonalities) of the original series.

frequency analysis is performed with a dilated, low-frequency version of the same wavelet.

There are two classes of wavelet transforms; the continuous wavelets transform (CWT) and its discrete counterpart (DWT). The DWT is a compact representation of the data and is particularly useful for noise reduction and data compression whereas the CWT is better for feature extraction purposes. To analyze the relationship between European electricity prices the continuous wavelet transform is used. In this part of the work we decompose the data series up to level 9.

The term wavelet refers to a small wave: small because the wavelet function is non-zero over a finite length of time (compactly supported) and wave because the function oscillates. Wavelet functions are constructed on the basis of location and scale parameters and a "mother wavelet" function. The mother wavelet ($\phi(t)$) is defined on the real axis and must satisfy the conditions $\int\limits_{-\infty}^{+\infty} \phi(t)dt = 0$ and $\int\limits_{-\infty}^{+\infty} |\phi(t)|^2 dt = 1$. These conditions imply that at least some coefficients of the wavelet function must be different from zero and that these departures from zero must cancel out.

The continuous wavelet transform, with respect to the wavelet ϕ, is a function $W_x(s, \tau)$ defined as:

$$W_x(s,\tau) = \int\limits_{-\infty}^{+\infty} x(t) \frac{1}{\sqrt{s}} \phi^* \left(\frac{t-\tau}{s} \right) dt \tag{1}$$

where * denotes the complex conjugate form. Wavelet coefficients are given by this transformation. The mother wavelet $\phi(t)$ serves as a prototype for generating other window functions. The term translation, τ, refers to the location of the window (indicates where the wavelet is centered). As the window shifts through the signal, the time information in the transform domain is obtained. The term scaling, s, refers to dilating (if $|s| > 1$) or compressing (if $|s| < 1$) the wavelet (controls the length of the wavelet). To extract frequency information from the time series in question, the mother wavelet is dilated or compressed to correspond to cycles of different frequencies. If the wavelet function $\phi(t)$ is complex, the wavelet transform W_x will also be complex. But this means that the transform can be divided into the real part ($\mathbb{R}\{W_x\}$) and imaginary part ($I\{W_x\}$), or amplitude, $|W_x|$, and phase[3], $\tan^{-1}\left(\frac{I\{W_x\}}{\mathbb{R}\{W_x\}}\right)$.

[3] The phase of a given time series $x(t)$ is parameterized in radians, ranging from $-\pi$ to π. Moreover, in order to separate the phase and amplitude information of a time series it is important to make use of complex wavelets. Just like the Fourier transform, under some regularity conditions, we can reconstruct $x(t)$ from its continuous wavelet transform (Torrence

Wavelets constructed over short time scales will tend to isolate sharp, high frequency volatility in the time series. Because of the short time scales, this information will have good time resolution but poor scale (frequency) resolution. Relatively long-scale wavelets will tend to capture low frequency volatility and will have relatively poor time resolution but good scale (frequency) resolution. This study uses the Morlet wavelet as the basis function used for wavelet transform (Percival and Walden, 2000).

2.1. Morlet wavelet

The Morlet wavelet allows good identification and isolation of periodic signals, as it provides a balance between localization of time and frequency (Grinstead, Moore and Jevrejeva, 2004). This is a complex wavelet, as it yields a complex transform, with information on both the amplitude and phase, essential for studying synchronisms between different time series. The Morlet wavelet in its simplified version is defined as:

$$\phi_{\eta}(t) = \pi^{-\frac{1}{4}} e^{i\eta t} e^{-\frac{t^2}{2}} \tag{2}$$

An important property of the Morlet wavelet is its accuracy, being the center of the wavelet ϕ defined by $\mu_t = \int_{-\infty}^{+\infty} t\,|\phi(t)|^2\,dt$ and its variance $\sigma_t^2 = \int_{-\infty}^{+\infty} (t - \mu_t)^2\,|\phi(t)|^2\,dt$.

The central frequency of a wavelet determines the waveforms, which are not close to zero within the window of the wavelet. The two peaks next to the central peak are half of its amplitude. The central frequency of the Morlet wavelet was chosen to be equal to nine since it gives a good balance between time and frequency localization. For this central frequency the Fourier frequency period $(1/f)$ is almost equal to scale.

The wavelet transform performs what is called time-frequency analysis of signals. In other words, it can estimate the spectral characteristics of signals as a function in time. The utility of wavelet analysis is that it can provide not only the time-varying power spectrum, but also the phase spectrum needed for computation of coherence.

2.2. Wavelet power spectrum, coherency and phase difference

The concept of coherence is fundamental and quite important in all fields dealing with fluctuating quantities. It is often defined as the action or fact of cleaving or sticking together (Oxford's English Dictionary). Correlation is defined as the relation of two or more time series, so we could say that those series that are highly correlated are coherent. The degree of coherence is a measure of how closely X and Y are related by a linear transformation. Thus, X and Y are closely related by a linear transformation if and only if their degree of coherence is close to its maximum value of unity. The two random variables X and Y are said to be completely coherent if and only if $|\rho| = 1$ and completely incoherent if and only if $|\rho| = 0$, where ρ is the correlation coefficient.

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and Compo, 1998; Conraria, Azevedo and Soares, 2008).

Dealing with discrete time series $\{x_n, n = 0, ..., N-1\}$ of N observations with a uniform time step δt, the integral in (1) has to be discretized, and the CWT of the time series $\{x_n\}$ becomes

$$W_n^x(s) = \frac{\delta t}{\sqrt{s}} \sum_{n=0}^{N-1} x_n \phi^* \left((n-m) \frac{\delta t}{s} \right), m = 0, 1, .., N-1 \tag{3}$$

It is possible to calculate the wavelet transform using this formula for each value of s and m but we can also identify the computation for all the values of m simultaneously as a simple convolution of two sequences (Torrence and Compo (1998) and Conraria, Azevedo and Soares (2008) provide more details on this). As also evidenced by these authors, when applying the CWT to a finite length time series we inevitably suffer from border distortions. This is due to the fact that the values of the transform at the beginning and at the end of the series are always incorrectly computed, involving missing values of the series which are then artificially prescribed. The region in which the transform suffers from these edge effects is called the cone of influence. In this area results must be interpreted carefully. Similarly to Torrence and Compo (1998) and Conraria, Azevedo and Soares (2008) the cone of influence will be defined here as the e-folding time of the wavelet at scale s, that is, so that the wavelet power of a Dirac δ at the edges decreases by a factor of e^{-2}. For the Morlet wavelet under analysis this is given by $\sqrt{2s}$.

The wavelet power spectrum is just $|W_n^x|^2$. It characterizes the distribution of the energy (spectral density) of a time series across the two-dimensional time-scale plane, leading to a time-scale (or time-frequency) representation.

The cross wavelet transform (XWT) of two time series x_n and y_n is defined as $W_n^{xy} = W_n^x W_n^{y^*}$, where * denotes complex conjugation and W_n^x and W_n^y are the wavelet transforms of x and y respectively. Let's us define the cross wavelet power as $|W^{xy}|$. The complex argument $arg(W^{xy})$ can be interpreted as the local relative phase between x_n and y_n in time frequency space.

Therefore, the wavelet power spectrum can be interpreted as depicting the local variance of a time series and the cross-wavelet power of two times series depicts the local covariance between these series at each scale or frequency. For more general data generating processes one has to rely on Monte Carlo simulations (see Conraria, Azevedo and Soares, 2008, for more details).

The phase for wavelets shows any lag or lead relationships between components, and is defined as

$$\begin{aligned} \phi_{x,y} &= \tan^{-1} \frac{I\{W_x\}}{\mathbb{R}\{W_x\}} \\ \phi_{x,y} &\in [-\pi, \pi] \end{aligned} \tag{4}$$

where I and $\mathbb{R}$ are the imaginary and real parts, respectively, of the smooth power spectrum.

Phase differences are useful to characterize phase relationships between two time series. A phase difference of zero indicates that the time series move together (analogous to positive covariance) at the specified frequency. If $\phi_{x,y} \in (0, \pi/2)$ then the series move in-phase, with the time-series y leading x. On the other hand, if $\phi_{x,y} \in (-\pi/2, 0)$ then it is x that is leading. We have an anti-phase relation (analogous to negative covariance) if we have a phase difference of π (or -π) meaning $\phi_{x,y} \in (-\pi/2, \pi] \cup (-\pi, \pi/2]$. If $\phi_{x,y} \in (\pi/2, \pi)$ then x is leading, and the time series y is leading if $\phi_{x,y} \in (-\pi, -\pi/2)$ (for this see Conraria, Azevedo and Soares, 2008). In other words, arrows at 0^o (horizontal right) indicate that both are in phase and arrows at 180^o (horizontal left) indicate that they are in anti-phase. It is important to point out that these two cases imply a linear relation between the considered series. Non horizontal arrows indicate an out of phase situation, meaning that the two series do not have a linear relation but a more complex relationship.

Cross-wavelet power reveals areas with high common power. Another useful measure is how coherent the cross wavelet transform is in the time frequency space. Following Torrence and Compo (1998) we define the wavelet coherency of two time series as

$$R_n^2(s) = \frac{\left|S\left(s^{-1}W_n^{xy}(s)\right)\right|^2}{S\left(s^{-1}\left|W_n^x(s)\right|^2\right)S\left(s^{-1}\left|W_n^y(s)\right|^2\right)} \tag{5}$$

where S is a smoothing operator in both time and scale. This definition closely resembles that of a traditional correlation coefficient, and it is useful to think of the wavelet coherence as a localized correlation coefficient in time frequency space. Without smoothing coherency is identically 1 at all scales and times. For the Morlet wavelet a suitable smoothing operator is given by

$$S_{time}\left(W\right)|_s = \left(W_n(s)^* c_1^{-t^2/2s^2}\right)|_s \tag{6}$$

and

$$S_{scale}\left(W\right)|_n = \left(W_n(s)^* c_2 \Pi(0, 6s)\right)|_n \tag{7}$$

where c_1 and c_2 are normalization constants and Π is the rectangle function. The factor of 0,6 is the empirically determined scale decorrelation length for the Morlet wavelet (Torrence and Compo, 1998).

The cross-wavelet coherence gives an indication of the correlation between rotary components that are rotating in the same direction as a function of time and periodicity[4]. Coherences near one show a high similarity between the time series, while coherences near zero show no relationship. It can be defined as the ratio of the cross-spectrum to the product of the spectrum of each series, and can be thought of as the local correlation between two CWTs.

Coherence is considered to be equivalent to correlation. Though, there are important differences between them. In coherence's calculation the signal is

[4] We use both cross-wavelet spectrums and coherence. In order to save space we only present the coherency and phase plots. Results of cross-wavelet spectrums will be provided upon request to the authors.

squared, thus producing values from 0 to 1. The polarity information is lost. By contrast, correlation is sensitive to polarity and its values range from -1 to 1. Coherence provides information about the stability of the true relationship between the two signals with respect to power asymmetry and phase relationship and not direct information about this relationship. Correlation, on the other hand, may be calculated over a single epoch or over several epochs and affected by phase, independently of amplitudes. The caveat is that this correlation may not be contemporaneous, but may involve a lead or a lag. A measure of the magnitude of this lead or lag is the phase lead.

The vectors plotted in the coherence pictures indicate the phase difference between the two series. Those pointing to the right mean that the variables are in phase. To the right and up with the first series lagging. To the right and down with the first series leading. Arrows pointing to the left mean that the variables are out of phase. To the left and up with the first series leading. To the left and down with the first series lagging. For a complete interpretation of the difference of phase between the analyzed series we suggest the reading of Barbosa and Blitzkow (2008, pp. 28-29) who interpret the meaning of the phase angels. However, we still need to know which of the time series is processed first for the scheme to be valid. In the present work, all pictures show the cross-coherency between two series. The name of the country presented first is our first series, the other one being the second we consider.

3. Data and descriptive statistics

For the empirical analysis we employ hourly time series of electricity spot prices registered in 6 European wholesale electricity markets. The time span for the considered markets starts in January 2000 and ends in August 2009, with a few exceptions at the start date (like France and Austria). The markets under analysis include the Nord Pool system (NP onwards, composed by Denmark, Finland, Norway and Sweden), Spain (OMEL), the Netherlands (Holand-APX), Germany (EEX), France (FR) and Austria (EXAA).

The electricity price series used in our study were obtained directly from the official websites. The data sets are composed by daily average hourly prices (24 hours average) of the spot electricity market and they represent the cost to obtain a certain quantity of electricity in a specific hour of the day. Price for the Nord Pool system is in NOK/MWh. All other prices are denominated in Euro per Megawatt hour.

Table 1: Descriptive statistics for electricity prices in the considered European countries

	APX	EEX	EXAA	FR	NP	OMEL
Mean	-2825,67	32,31	36,12	37,92	138,62	29,23
Std. Dev.	4537,87	18,72	206,23	22,61	73,12	9,40
Skewness	-0,95	3,91	-48,16	3,25	0,53	1,42
Kurtosis	1,90	37,28	2343,85	26,96	3,07	8,22
JB	479,69	123336,70	5.48E+08	61485,05	112,42	3523,65
p-values	(0,00)	(0,00)	(0,00)	(0,00)	(0,00)	(0,00)

Note: The table reports means, standard deviation, skewness, kurtosis, and the Jarque-Bera (JB) test for normality. The values in parentheses are the p-values. APX – Netherlands; EEX – Germany; EXAA – Austria; FR – France; NP – Nord Pool; OMEL – Spain.

The examination of values in table 1 indicate that mean prices for all electricity spot markets are positive except for APX. The Jarque-Bera statistic indicates that the distribution of prices, for all samples, has fat tails and sharper peaks than the normal distribution. All price series exhibit excess kurtosis.

The high kurtosis values show that the available time series are in fact peaked relative to a normal distribution. This may happen due to weather conditions, outages, the fact that electricity cannot be stored and has to be consumed at the same time as it is produced, the exploration of market power (due to the fact that some sections in the market may become isolated from the rest of the market - transportation constraints can also be implying this isolation), some change in the surrounding environment (external factors like economic behavior around the world or the change of market rules of their own electricity markets), among other causes.

There are some markets with tremendous volatility like Austria and the Netherlands, and significant differences are apparent between the average wholesale electricity prices among the six markets, mostly notables in Austria and Nord Pool. The reason for this is attributed to agents learning by Simonsen (2003) and Haldrup and Nielsen (2006).

The mix of generation technology has an impact on both the mean and standard deviation of market prices (Wolak, 1998). He argues that prices in the market dominated by fossil fuel or thermal plants technology tend to be much more volatile than the prices in the markets dominated by hydroelectric capacity (Nord Pool and EXAA). However, given the data we have available we are not able to confirm this finding.

As can be observed by table 2, the electricity markets under analysis differ on their underlying production structure, and despite the recommendations throughout "green markets" they show little evolution in time (considering 2000 and 2007) with respect to hydro. In fact, in all markets there is a decrease in percentage terms of the electricity generated by hydro from 2000 to 2007. As such, renewables are not the main production source in the majority of electricity markets. With the sample analyzed here, Austria and Nord Pool markets (represented in table 2 and 3 by Norway, Finland, Sweden and Denmark) are the exception.

Table 2: Electricity generated by source (percentage of the total electricity generated)

Source		GR	SP	FR	NT	A	F	S	N	D
Hard Coal	2000	25,05	32,37	4,92	25,22	7,21	12,19	1,12	0,03	46,25
	2007	20,76	22,66	4,29	24,13	9,88	17,19	0,44	0,04	50,82
Hydro	2000	4,54	14,13	13,39	0,16	70,71	20,95	54,00	99,47	0,08
	2007	4,47	10,16	11,26	0,10	60,67	17,45	44,47	98,24	0,07
Natural Gas	2000	9,18	9,36	2,13	57,71	12,64	14,40	0,32	0,15	24,34
	2007	11,51	30,50	3,86	57,18	15,56	12,98	0,52	0,53	17,65
Nuclear	2000	29,67	27,63	76,78	4,38	0,00	32,12	39,37	0,00	0,00
	2007	22,06	18,17	77,17	4,07	0,00	28,83	44,99	0,00	0,00
Petroleum	2000	0,84	10,06	1,33	3,49	2,77	0,87	1,19	0,01	11,78
	2007	1,77	6,10	1,08	2,15	2,02	0,58	0,72	0,02	2,82

Note: Values are in percentage. GR – Germany; SP – Spain; FR – France; NT – Netherlands; A – Austria; F – Finland; S – Sweden; N – Norway; D – Denmark. Source: Euronext and own computations.

The shape of the system marginal cost function is also influenced by the productive mix of the generation side of the market. Nord Pool's production mix relies mainly on hydro and nuclear, being gas and coal mostly used by Denmark in this regional European market. Also the Austrian market bases his production on hydro having 70,71% of his total electricity generated in 2000, whose value decreased to 60,67% in 2007.

France, Spain and Germany have a large nuclear production, being followed by coal in Germany and Spain, and by hydro in France. The Netherlands has a small quota in hydro production, but a large one in coal and gas.

We also need to analyze the concentration in the industry since it was one of the main objectives of the EU Directives: increasing competition to reduce market power. Table 3 presents the percentage share of the largest generator in each of the considered markets in 2000, 2004 and 2008. The Nord Pool market is represented in table 3 by the last four listed countries.

Table 3: Percentage share of the largest generator

Country	2000	2004	2008
Germany	34,0	28,4	30,0
Spain	42,4	36,0	22,2
France	90,2	90,2	87,3
Austria	32,6	-	-
Finland	23,3	26,0	24,0
Sweden	49,5	47,0	45,2
Norway	30,6	31,2	27,4
Denmark	36,0	36,0	56,0

Source: Euronext historical data

As evidenced by the data, the French market is characterized by the highest level of concentration, while Spain, Finland and Norway by the lowest. In general, all markets have a lower concentration in 2008 than they had in 2000 being the exceptions Germany and Denmark. As such, we may conclude that in these considered markets, the level of concentration is still high which creates the scope for market power and the consequent influence in spot prices. Uncertainties about power markets, high costs associated with the distribution and production plants for those who plan to start, and the prevalence of incumbent operators, are the possible main causes behind this lack of full competition until the present moment.

4. Empirical Results

With this work we want to illustrate how relationships between electricity price series change over time and across different frequencies. In fact, wavelets allowed us to detect transient effects which would be very difficult to detect using classical econometric techniques. In order to sustain previous results regarding the correlation analysis we extend in this section such analysis by means of the Coherence Morlet wavelet analysis.

The correlation analysis developed in the previously mentioned works indicates the possibility of a certain relation between two time series, however, this is of global nature and does not furnish us precise information about when such a relation occurs: the fact that two data series have similar periodicities does not necessarily implies that one is the cause and other the effect; besides, even if the correlation coefficient is very low, that does not means that there is no relation. In fact, there is the possibility that such a relation could be of non-linear nature, or that there is a strong phase shift.

A way to analyze two non-stationary time series, to discern whether there is a linear or non linear relation is by means of the Coherence Wavelet method. This furnishes valuable information about when and which periodicity do coincide in time, and about its nature (linear or non linear relation). It is especially useful in highlighting the time and frequency intervals where two phenomena have a strong interaction. The coherence between two or more time series can be used to measure the extent to which multiple time series move together.

Although not presented here we have started by computing the wavelet power spectrum for each of the electricity price series under analysis[5]. By a first visual inspection at the time scale decompositions of the series, we can observe that most of the action in these occurred at high scales (low frequencies).

We should also mention why we do not pay so much attention to the wavelet cross-spectrum. This describes the common power of two processes without normalization to the single wavelet power spectrum. This can produce misleading results, because we are essentially multiplying the continuous wavelet transform of two time series. In this way, if one of the spectra is locally flat and the other exhibits strong peaks, this can produce peaks in the cross spectrum,

[5] Although not presented here due to space restrictions, results will be provided upon request.

while may have nothing to do with any relation of the two series. Since the information able to be extracted from these pictures need to be analyzed with caution, we concentrate the rest of the work to the analysis of wavelet coherency (see Conraria, Azevedo and Soares, 2008, for more details).

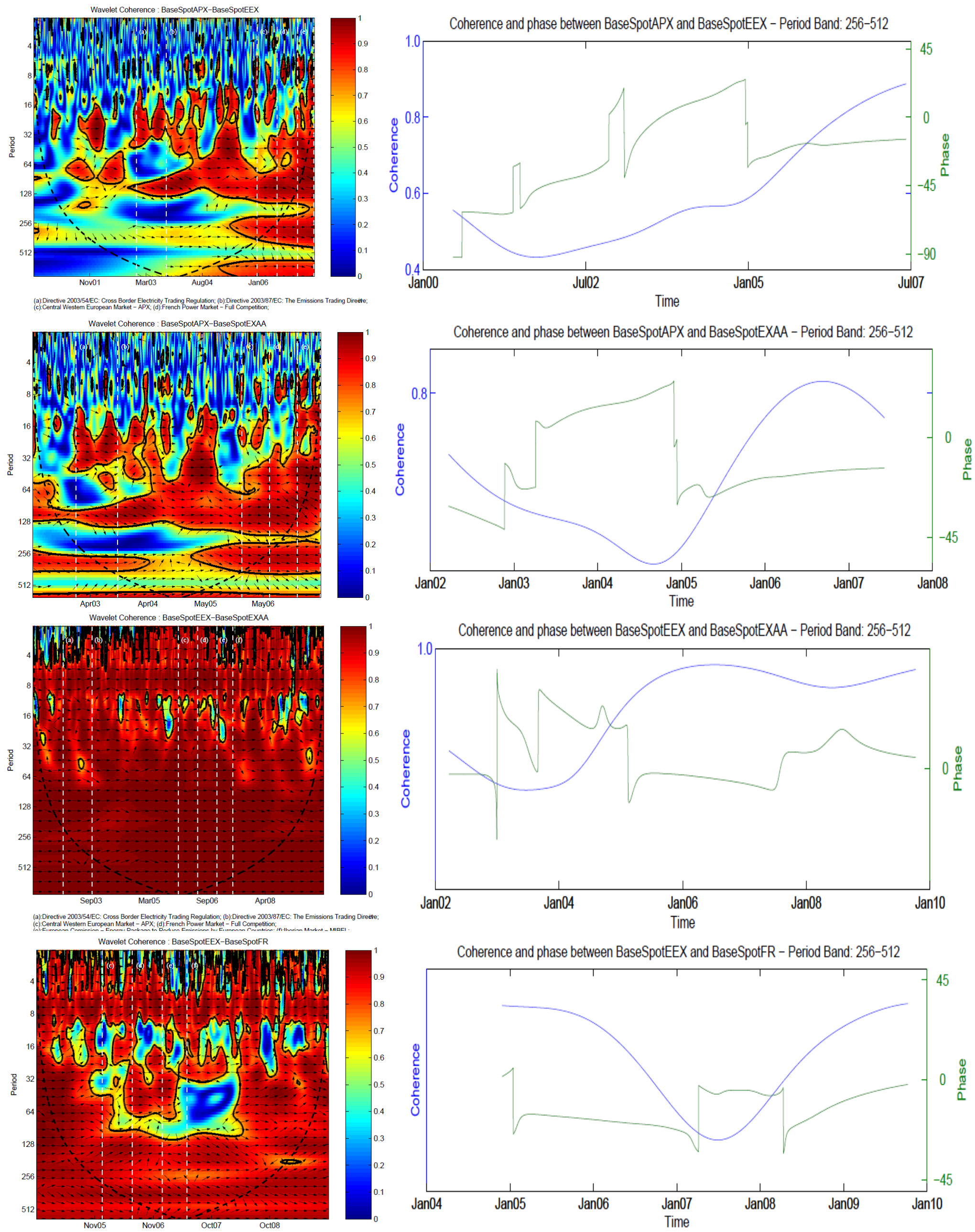
In figures 1, 2 and 3 we can see two pictures. the one's in the left present the estimated wavelet coherency and the phase difference arrows between the six markets under analysis. Contours denote wavelet-squared coherency, whereas the thick black contour is the 5% significance level, where the values for the significance were obtained from Monte Carlo simulations. Outside the thin line is the boundary affected zone. The cone of influence, indicating the regions affected by hedge effects, is shown with a dotted line. The phase difference between pairs of series is indicated by arrows. Those pointing to the right mean that the variables are in-phase. To the right and up with the first series (in the order they appear in the bottom of the graph) lagging. To the right and down with the first series leading. Arrows pointing to the left mean that the variables are out-of-phase. To the left and up with the first series leading. To the left and down with the first series lagging. Color code for power ranges from light grey (low coherency, near zero) to dark grey (high coherency, near one).

Plots in the right of these figures show the coherence and phase of countries which are compared pairwise. It's simply a more detailed analysis of the left plots. These pictures show values of coherence varying between zero and one (vertical axis). Values of phase are calculated to each value of frequency and it varies between -π and π. In the horizontal axis we have the time period. On the right the calculations are done for the 256-512 days frequency band, which was showed to be the region with higher commovement among the series by the plots on the left of the wavelet coherency.

Looking at figure 2 wavelet coherency plots, in the left, we see some statistically significant regions at high and medium frequencies (low and medium scales) between Nord Pool and the other European electricity markets. In most of these regions, arrows point straightforwardly to the right, meaning that both series are in phase, and to the right and up meaning that the first series (NP) is lagging. We see a significant changing behavior in arrows between NP and Spain (OMEL) after Directives 2003/54/EC, for cross-border electricity trading regulation, and 2003/87/EC for the Emissions trading scheme, have been implemented. Until then arrows pointed to the left and up (NP leading), after they point right and up and right and down (meaning that both series turned out to be in phase, with NP leading). But this behavior between the two markets is mostly notable at lower frequencies, with a highly significant region noticed after the creation of the Iberian electricity market (MIBEL) in 2007. Moreover, NP and EEX series are showed to be mostly in phase, especially in the 4-8 days frequency band, having the same behavior been noticed between NP and Powernext. However, the relation between NP and APX shows to be weak independently of the time scale analyzed.

As for the other markets we see a significant behavior change among the series after 2003. The exception is provided by the OMEL market (figure 3) with relation to all the other European countries. In fact, we can observe highly statistically significant regions (islands of high coherency and statistically significant), especially at medium-high-scales between APX, EEX, EXAA and Powernext (figure 1 and 3). APX price series show an in-phase behavior with all the other markets, especially with France (meaning that they have a linear relation, at least in the high coherency regions). We should not forget the launch of the Central Western European market (France, Belgium and the Netherlands) in 2006. Moreover, information on the phases show us that the relationship has been homogeneous at medium and high scales, while not being homogeneous at high frequencies with arrows pointing in different directions.

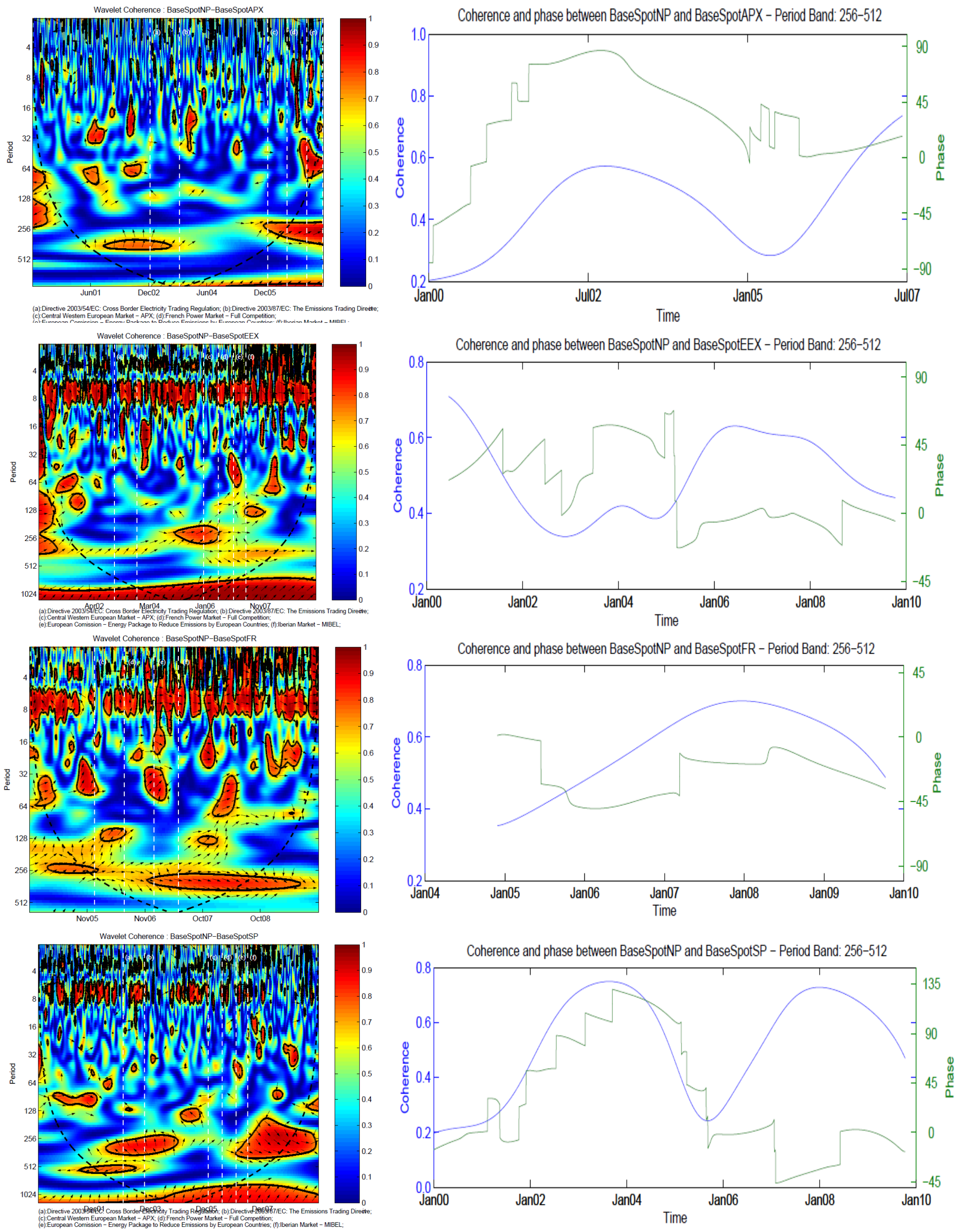
Figure 1: Wavelet coherency plot between pairs of electricity price series in the considered six European electricity markets



From all the markets under observation, the Spanish market shows, by the wavelet coherency, the lowest commovement with all the others, although most of the higher coherency with those geographically closer. This is evident at higher frequencies, even with some regions of high common power showed in medium scales.

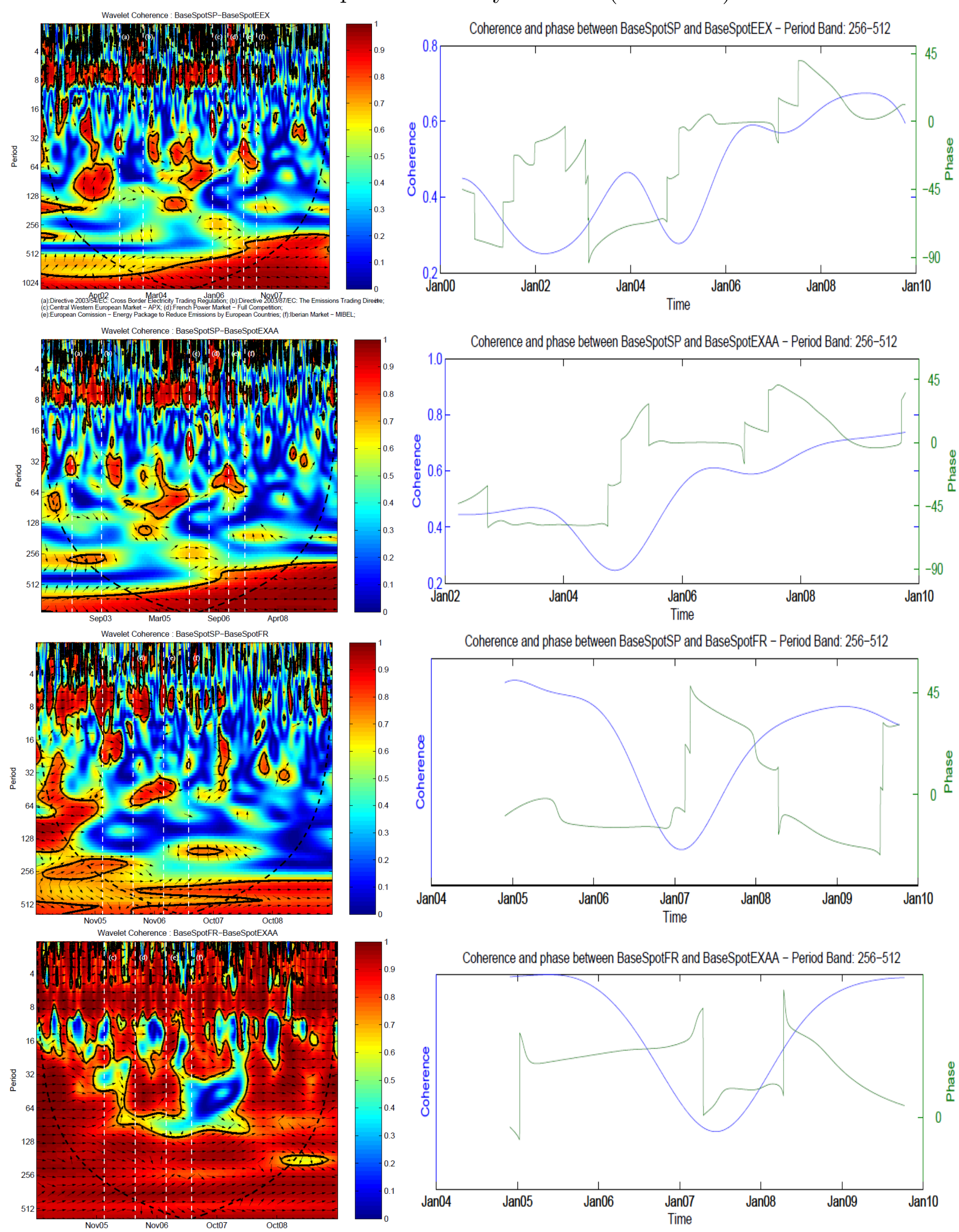
France installed 58 nuclear power plants between 1970 and 1993, while being a huge exporter of electricity. This policy made of France a low-cost area for electricity as compared to the Netherlands, for example, that relies mostly on natural gas. With Spain, the situation is more variable and depends on the rainfalls in the Iberian Peninsula. As such, only during rainy periods Spain is able to export to France, importing much of the time from this country. We should also emphasize the fact that the Iberian market is very distant from all the other markets, having France as the most direct "client". This may thus explain the observed results presented by the cross wavelet coherency pictures in figure 3.

Figure 2: Wavelet coherency plot between pairs of electricity price series in the considered six European electricity markets (continued)



It should also be emphasized the relation between Germany and the Netherlands, Germany and France, and between France and the Netherlands. By the wavelet coherency plots, and given that wavelet coherency is used to identify both frequency bands and time intervals within which pairs of series are covarying, we see that these series show high statistically significant coherency and an homogeneous behavior (they are all in-phase; a linear relationship is found between the series) independently of the frequency-scale. There are however a few exceptions in the 8-16 days, 16-32 days and 32-64 days scale for EEX-FR (figure 1) and FR-EXAA (figure 3). In these countries case, short and long-run movements are highly correlated, meaning that country specific phenomenons are rapidly transmitted to the other markets. These countries have a very similar wavelet transform, which implies that these 3 countries share the same high power regions between them, and also that their phases are aligned. As such, the contribution at each frequency to the total variance is similar between them: it happens at the same time where ups and downs in electricity spot price series occur simultaneously. So, we can say that a value very close to zero between countries phase indicate that price series/markets are highly synchronized, with the phase difference revealing a very stable and strong relation. By the plots on the right we see specific periods where this has occurred.

Figure 3: Wavelet coherency plot between pairs of electricity price series in the considered six European electricity markets (continued)



However, it is clear that the different series still have different characteristics in the time-frequency domain in European electricity markets. This can be summarized by looking at the phase and phase difference between series, pointing for the lack of full market integration (which agrees with Zachman, 2008, results).

We observe that Nord Pool and Spain do not exhibit many regions of high coherency with the other European countries, and that their phases are not very stable when compared to those attained by Germany, France, Austria and the Netherlands (in accordance to the results achieved by Bosco et al., 2009). The fact that more regions of high coherency appeared after 2003 suggests that it was from that moment onwards that they start approaching together, which also means that the Directives were starting to produce their desired effects on the European electricity markets. We may not also forget that these last four countries are those geographically closer and with a great developed capacity in terms of border connections. That's why that for EEX-EXAA, EEX-FR and FR-EXAA series we can argue that commovement and cointegration is a reality now.

While the phase difference gives us information about the delay, or synchronization, among oscillations of pairs of time series, the coherency cross-wavelet transform will tell us if this correlation is strong or not. Regions of high coherency between two countries are synonym of strong local correlation.

With the analysis of the right plots we will focus on the details provided by coherence and phase. In general phases are not very stable, and there are countries which do not exhibit many regions of high coherency, especially before 2005. Results suggest that taking out the year 2005, coherences were in general high among the series.

From the phase plots at the 252-512 days frequency, coherency fell to lower values in the year 2005. During the year 2005 until the summer 2006, we had a period of high natural gas prices (record natural gas demand for electric generation and continued because of damage done by hurricanes Katrina (August 2005) and Rita. According to the European Energy Markets Observatory 2005 report, this was a period of high energy prices, an overall decrease of peak generation margins, slow progress in interconnections and insufficient infrastructures investments. They also state that "The recently established Emissions Rights trading market experienced great volatility due mainly to a lack of EU countries' coordination in publishing their 2005 results and in their comparison to the National Allocation plans. This in turn has influenced wholesale electricity prices." EXAA, APX, Finland and Denmark all rely on natural gas, Spain and Denmark are the one's that use more petroleum for electricity generation. In accordance with the same report, high prices in the year 2005 were due to: an higher demand from emerging countries, like India and China, and North America; due to geopolitical crisis like the Iraq and Iran crisis; due to the civil war in Nigeria; the lack of investment in exploration, production and refinery; the Katrina and Rita hurricanes on Gulf of Mexico oil platforms; and financial speculation.

The high summer temperatures in 2005 and low rainfall in Spain and France, and the cold weather during the winter of 2005/2006 have also contributed to these high prices observed. Peak price spikes were seen in Germany and France, given that when the cold wave hit Europe in November 2005, 5 nuclear plants in France and 2 in Germany were unavailable, and also the hydro reservoirs in France were at their lowest levels. In the Nordic countries hydrological levels were very good during winter 2005 and NordPool was Europe's sole exchange provider of low wholesale hydro power. Countries such as Spain, with high dependency on gas supply for power plants and limited substitution capacity to other type of generation capacity faced significant instabilities in their power markets during 2005. Others like Germany and the Netherlands have a better balance between gas-fired and coal-fired plants and were able to switch to coal. Countries such as France with a high portion of nuclear generation were less impacted. The report of the European Energy Markets observatory also states that during this period several markets are "naturally" converging like the German and French power market, where prices were 99,69% correlated in 2005.

EEX, EXAA, France and Austria show more regions of high coherency in the sample period suggesting that they are approaching each other. We see the phase of EEX-FR and EEX-EXAA close to zero (figure 1), especially in the period January 2005 - January 2008. Since a phase difference of zero indicates that the series move together (analogous to positive covariance) we can say that they started to move together from 2005 onwards although not being a perfect move. Even so, at higher frequencies both phase and coherence showed a very erratic behavior[6].

In figure 1 (APX-EEX), looking at the phase difference in the 256-512 days band we can see a negative relation between both series for most of the time. At large scales the phase has been between 0 and $-\pi/2$, which means that the series move in phase with EEX leading APX. In both pictures coherency has been increasing with an evident trend. Only in the period January 2006 to January 2009 the phase of zero indicates that the time series SP-EEX move together (figure 3).

Only in some countries coherence is near one, but the increase in coherence after 2006 is evident in all of them. Nevertheless, there are groups of countries that present high values of coherence (SP-FR; EEX-EXAA; APX-EXAA; FR-EXAA) for specific periods of time, namely the last two to three years (2006-2009). In these cases, phases are close to zero whereas the coherence is close to one. This result indicates that probably there exists synchronization inside these groups for specific time periods. Although we may not forget that these plots are for high scales (lower frequencies). On the other side, couples of countries formed by other combinations present lower of coherence and their phase is generally different from zero.

From figure 1 we see that EEX leads EXAA, while France leads the German market for the entire sample period. APX has been leaded by Germany and the Netherlands from 2005 onwards. From figure 2 we can infer that NP has

[6] Results are not presented here but will be provided upon request.

been leading all the other countries price series except France. Between 2003 and 2005 NP was leading SP but we have an out-of-phase relationship between both in this time period. Finally, figure 3 results point out that France has been leading the Netherlands market for the entire sample and that Spain only leads the other 3 closest markets between 2007-2008 at the 256-512 days frequency band.

It is interesting to note the variability presented in the phase plots and that the number of cycles at each frequency has changed mainly from 2006 onwards. It is then fair to say that the phasing is not well synchronized. In sum, coherence and phase at higher frequencies is less consistent, which impels the synchronicity of the series[7]. However, coherence showed to be higher for lower frequencies except during the year 2005.

The presented results may be due to the special features describing these markets, but also to the remaining obstacles to the full implementation of EC Directives. The generation mix that still persists among these markets (that impact costs), the high market power that is still evident (as explored previously) and transmission capacities of electricity interconnection lines limited for legal or technical reasons, and the cross-border trade costs associated, may be the reason why the wavelet coherency among all pairs of countries do not show a strong commovement among them independently of the scale/frequency. The lack of lively cross-border trade is mainly due to the lack of sufficient capacity, and frequent physical congestions (Zachman, 2008).

As pointed out by Zachman (2008) and Bosco et al. (2009), the cross-border trade in electricity is still facing various impediments that slow down the process of the creation of a single European electricity market.

In sum, there are still large wholesale price differences between countries in Europe, being interconnection capacity scarce across Europe, and despite the old 2003 Directives and third energy package published by the EC in January 2007, little progress has been made in this direction (see Dobbeni, 2007, for more details). According to the objectives proposed by the European Council in 2002, all Member States should be able to import at least 10% of their installed generation capacity which is still not the case for Spain, among other countries which were not included in the present study.

Since Germany shows a strong coherency behavior with France and the Netherlands, maybe it should be the time to join the Central Western European market initiative. In fact, given that the European Commission realized what was happening in some regions in terms of connections, they start promoting a regional strategy for all regions as an intermediate step towards the desired single electricity market in Europe. However, large differences persist in terms of production mix, market power is still evident and interconnection capacity operating fully and in a transparent manner is still lacking.

Despite, the desire of the "unique market" is still an illusion; very important

[7]Results for coherence and phase plots revealed to be very unstable at higher frequencies. Moreover the highest comovement among the series was revealed for lower frequencies. As such we only present the coherence and phase for the 256-512 days frequency band, which is the most representative of the message we are trying to pass.

steps have been given in the direction of harmonization and coordination of market rules and operations. The most important steps are observed by the regionally integrated markets: the Nordic, the Central Western European and the Iberian market. Now, it is time to start integrating these regional segments into a common one, although the ambitious target of a single common European electricity market is far from being a reality at the moment, as evidenced by the empirical results we have provided here.

We have also seen that differences still exist in the productivity structure of the analyzed countries, reflecting different cost and prices volatility, generally due to hydro and nuclear ratio production for each country. Moreover, energy markets also show disparities in terms of total share of the largest producer (Commission of the European Communities, 2009). The variability presented in the phase plots and the number of cycles at each frequency has changed mainly from 2006 onwards (the phasing is not well synchronized). Coherence among the series was showed to be high for lower frequencies except during the year 2005, mainly due to extreme weather conditions that hit Europe and countries limited substitution capacity to deal with this problem.

As for now, and in accordance with previous author's results (Zachman, 2008, and Bosco et al., 2009) we reject the assumption of full market integration. Our results show that France, Germany, the Netherlands and Austria electricity markets are highly integrated, but that Spain and Nord Pool do not share the same commovement with the rest of the European electricity markets despite the change of behavior in the most recent years (as evidenced by the statistical significant regions of high common power in wavelet coherency plots and phase analysis). As for now, these six markets work well as regionally integrated markets, not as a common/single European group, since structural differences are still persistent among them.

5. Conclusions

In this work we revisited the study of European electricity markets comovements resorting to a simpler and less demanding, in terms of data treatments, technique known as wavelet analysis. Using this, we were able to confirm previous empirical findings that the single desired European electricity market creation is still in a very infant stage, although there are some regions inside Europe where we can now say they are converging (the Central Western European market). This price divergence, which contradicts the initial idea of a single common market, finds some reasonable explanations, namely, limited cross-border transmission capacities and different market opening degrees.

The main focus of this research is on the time/frequency evolution of price electricity series behavioral changes. In accordance to previous empirical findings we reject the assumption of full market integration but we show that some markets are working well as regionally integrated markets. France, Germany, the Netherlands and Austria electricity markets are highly integrated, but Spain and Nord Pool do not share the same commovement with the rest of the European electricity markets despite the change of behavior in the most recent years.

As for now, we reject the assumption of full market integration, being this most noticed at geographically closer countries and at lower frequencies. We were also able to see some change in the behavior of the analyzed series from 2003 onwards in some countries, maybe due to the start of Directives implementation.

Moreover, we provide evidence for the changing behavior of electricity price series through time and at different frequencies. Empirical results attained in this work allow us to say that at the longest wavelet scales, the wavelet correlation coefficients exceed substantially unconditional correlations. The shorter the time scale (high frequencies) the smallest the number of significant comovements of electricity spot prices in Europe. Moreover, the magnitude of the comovements increases as the wavelet time scale increases.

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