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Analysis of volatility transmissions in integrated and interconnected markets: The case of the Iberian and French markets.

A. Ciarreta* and A. Zarraga†

Abstract

This paper models the mean and volatility spillovers of prices within the integrated Iberian and the interconnected Spanish and French electricity markets. Using the constant (CCC) and dynamic conditional correlation (DCC) bivariate models with three different specifications of the univariate variance processes, we study the extent to which increasing interconnection and harmonization in regulation have favoured price convergence. The data consist of daily prices calculated as the arithmetic mean of the hourly prices over a span from July 1st 2007 until February 29th 2012. The DCC model in which the variances of the univariate processes are specified with a VARMA(1,1) fits the data best for the integrated MIBEL whereas a CCC model with a GARCH(1,1) specification for the univariate variance processes is selected to model the price series in Spain and France. Results show that there are significant mean and volatility spillovers in the MIBEL, indicating strong interdependence between the two markets, while there is a weaker evidence of integration between the Spanish and French markets. We provide new evidence that the EU target of achieving a single electricity market largely depends on increasing trade between countries and homogeneous rules of market functioning.

Keywords: electricity price markets, multivariate GARCH, volatility spillovers
JEL classification: C32, C51, Q49

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1 Introduction

The European Union (EU) has the ambitious target of fully integrating national energy markets by 2014. Market integration seeks to encourage more intense competition and security of supply. The progressive harmonization of electricity market rules is at the heart of promoting an effectively competitive internal market and delivering benefits to electricity customers and opportunities to generators and electricity traders.

Although the target date is fast approaching, electricity markets in Europe are not actually harmonized. Some progress has been made since the first steps were taken with the passing of Directive 96/92/EC, which set common rules for the construction of the single European electricity market by which country members must favour the interconnection and interoperability of systems. However, this directive was not very successful because the degree of openness and speed of reforms was very uneven. Moreover border electricity trade did not increase significantly in the years following the adoption of the directive, thus jeopardizing the ultimate goal of building a single market and remaining limited to creating national liberalized electricity markets. Finally, Directive 2003/54/EC established "common rules for the generation, transmission and distribution of electricity". It also defined procedures regarding network operations but set no further targets on interconnections.[1] In 2007, the European Commission published its third energy package: It identified the lack of electricity market integration as one of the factors that results in distortions to competition. This mainly results from insufficient interconnecting infrastructure between national grids, insufficient incentives to improve cross border infrastructures, inefficient allocation of existing capacities, and incompatible market design between transmission system operators (TSO) and spot market operators (SMO).[2]

Much work still needs to be done with respect to aligning national market and network operation rules as well as making cross-border investment in energy infrastructure. However, despite this general framework regional market integration has already been launched: MIBEL, which integrates Spain and Portugal, and EPEX, which integrates France, Germany, Austria and Switzerland (a non EU country) are two examples. Our aim here is to analyze price volatility transmissions between bordering countries, with reference on the one hand to the integrated Iberian electricity market and on the other hand the situation between the interconnected Spanish and French electricity markets, for the period July 1st, 2007 to February 29th, 2012. It is possible that shocks in one country may be transmitted to distant non-bordering markets, i.e. from France to Portugal, however we would

[1] See Jamasb and Pollitt (2005) for an early review of the process towards market integration in the EU countries and the identification of regional markets.

[2] These conclusions among others related to national market structural rigidities were published in the Sector Inquiry into the energy sector conducted by the DG COMP in 2007.

expect this to be a second-order effect and computationally costly.

The peculiarities of power are reflected in the characteristics of the prices. Once electricity has been produced there is little possibility of storing it. As a result prices show explicit intra-day patterns that vary with the season. Moreover, – due to grid constraints – the price can differ between regions and countries. Most of the relevant literature concentrates on stochastic price models that account for seasonal-adjusted log-prices. These periodic within-day, week and year patterns influence prices and estimations must be controlled to circumvent bias in estimation. Furthermore, electricity price volatility has a marked variability in time. It is not uncommon to find time series of prices with sharp price spikes within the day, although overall mean reversion is observed. Another feature is that electricity spot prices exhibit long memory behavior. Finally, the fact that markets are becoming increasingly interconnected implies that there is room to analyze price shock transmissions between markets.

Several studies take the line of supporting the interdependence hypothesis between electricity markets, although the econometric methods used are different. One strand of literature uses vector error correction models, cointegration and Granger causality methods in the study of the dynamic relationships between electricity prices from different markets and time periods (see De Vany and Walls, 1999a, Park et al., 2006 and 2008, Ferkingstad et al., 2011, Moutinho et al., 2011 or Bunn and Gianfreda, 2010, among others). Another strand studies and models spot price volatility using volatility models such as jump diffusion and regime switching models as proposed by Weron et al. (2004). The starting point is a stochastic differential equation that includes mean reversion and jumps. Other papers, following similar econometric methods include Huisman and Mahieu (2003), Bierbrauer et al. (2004), Haldrup and Nielsen (2006), Higgs and Worthington (2008) and Lindström and Regland (2012), among others.

There are other studies at country level that use various models of the GARCH family to capture dynamics and volatility in markets with high frequency data. These models are widely used for modeling the volatility of financial assets because they are capable of capturing the main empirical features observed in the volatility, measured as the conditional variance[3]. However, it is also accepted that financial assets and electricity prices share empirical features which make it appropriate to use GARCH models for electricity price series. Some examples can be found in Sadorski (2012), who finds volatility spillovers between oil prices and the stock prices of clean energy companies and technology companies. Nomikos and Andriosopoulos (2012) fit GARCH models to spot prices in the eight energy markets that trade futures contracts on NYMEX, though they do not analyze for spillovers between markets. Malo and Kanto (2006) fit several multivariate GARCH (MGARCH) models to daily NordPool closing prices for spot and futures contracts between 1996 and 2002. Worthington et al. (2005) perform a study

[3] See for example Byström (2003), Syllignakis and Kouretas (2011), Weber and Zhang (2012), Kim et al. (2005) and Nomikos and Andriosopoulos (2012).

for the NEM Australian market to assess whether the target of a nationally integrated and efficient electricity market is being achieved, using data from 1998 to 2001. The market accounts for five electricity spot markets. Despite the existence of NEM, regional electricity spot markets are not fully integrated. Nevertheless, shocks or innovations in particular markets still exert an influence on price volatility. Later, Higgs (2009) models price and volatility in the same market for the extended period 1999 to 2007, involving four integrated sub-markets. She finds strong interdependence between markets which are well-connected and weaker effects when they are not. Denny et al. (2010), using a stochastic model, show that increased interconnection should reduce average prices and the variability of those prices in a country with a large installed wind power capacity. However, increased interconnection does not necessarily reduce excess wind power generation because priority is given in the daily scheduling decisions to renewable generation.

The methodology used in this paper is based on MGARCH models, which allow the study of volatility transmission between different markets and can help to understand better the differences between interconnected and integrated markets through the analysis of the presence and degree of interdependence between them. Bivariate constant and dynamic conditional correlation models in which seasonal effects are taken into account are estimated and compared to select the best ones for modeling electricity prices in the MIBEL and Spanish and French electricity markets.

The paper is structured as follows. Section 2 explains the interconnection structure and the trading between Spain and France and Spain and Portugal. Section 3 presents the data and provides some descriptive statistics. In Section 4 the methodology is described and in Section 5 we summarize the results. The paper concludes with some implications of the study.

2 Markets and Interconnections

Spain began liberalization in 1998 when the market operator *OMEL* was launched. Portugal joined Spain in July 2007 to create the integrated Iberian electricity market operated by *OMIE*. Until then, based on European targets, each country developed its own transmission network and their systems were interconnected at a few strategic points along the border. Market rules say that generators sell electricity to meet demand across the interconnected power systems, which are constrained by the available capacity. Therefore, there are two possibilities: if there is no congestion in the grid there is a single price for both countries. However, if there is congestion then there is market splitting and the system operator schedules cost efficient plants to cover the demand.

France launched the *Powernext* Day-ahead market in November 2001. In 2008 there was a transfer of Powernext Day-Ahead, Powernext Intraday, market coupling staff and activities into the EPEX Spot SE. In Spain and France transmission is governed by capacity allocation rules. Auctions are organized jointly in both directions by the TSOs. However, separate auctions are implemented in each direction.

The achievement of a single market depends largely on the existence of well-developed interconnections that allow for spillovers between markets. Table 1 summarizes yearly basic market structure characteristics for each country and year; generation capacity (MW) and capacity of interconnections (MW), within MIBEL and between Spain and France. We take Spain as the reference country, thus M stands for the maximum import capacity of Spain from either France or Portugal and X stands for the maximum export capacity from Spain to either France or Portugal. All the values reported bellow are from the annual reports of the TSOs.

Table 1: Market structures

	Installed capacity			Interconnexions[a]			
				SP-FR		SP-PO	
	FR	SP	PO	M	X	M	X
2007	115,938	86,323	14,123	1,400	300	1,700	1,600
2008	117,628	90,915	14,899	1,400	500	1,700	1,600
2009	120,434	94,561	16,625	1,400	600	1,700	1,600
2010	123,783	99,043	17,912	1,400	700	1,700	1,900
2011		100,168	18,914	1,400	1,000	2,400	2,400

[a] Maximum values taking into account the unavailability of the network.
FR-France, SP-Spain and PO-Portugal. M-imports and X-exports.
Source: REE in Spain, RTE in France, and REN in Portugal.

The target set in 2005 of an import capacity of at least 10 percent of installed generation capacity for each country had not been reached in Spain or France in 2011. By then, total import capacity of Spain was at most 4400 MW, which is 4.4 percent of the total installed capacity. Thus, Spain is far from reaching the target set in 2005. In the case of Portugal, the only interconnection is with Spain and the share is at most 12 percent, well above the limit. The maximum import capacity between Spain and France has remained stable whereas export capacity has significantly increased.

We illustrate the extent to which there is correlation between prices and electricity flows. Figures 1 and 2 plot net selling positions and differences in prices in both interfaces. Since the reference country is Spain, positive (negative) values of the electricity flows indicate that Spain is a net importer (exporter) of electricity, and a positive (negative) price difference indicates higher prices in Spain than in France or Portugal.

Figure 1: Monthly net trade and price differences. Spain-Portugal

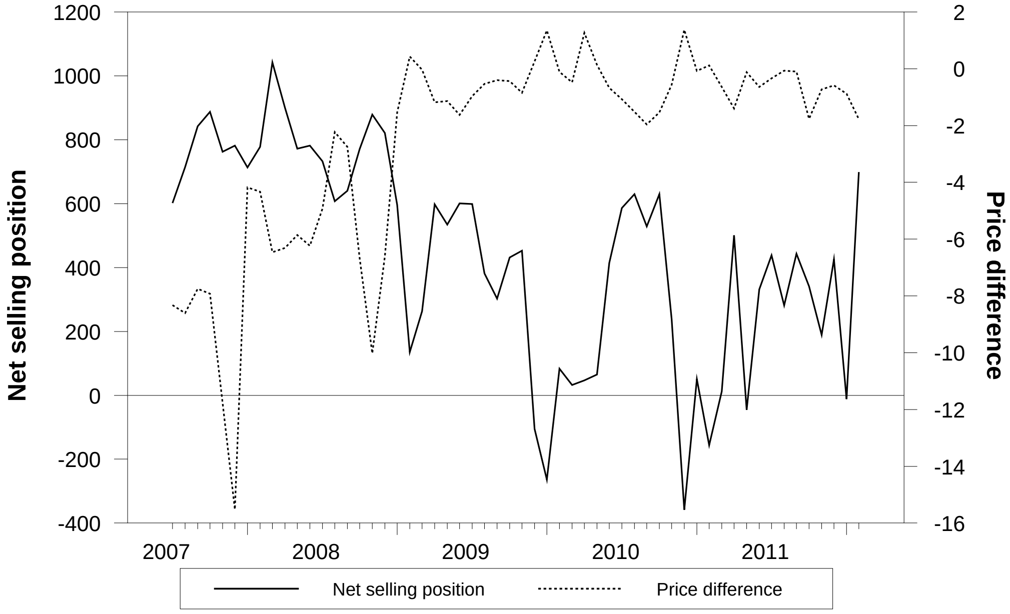
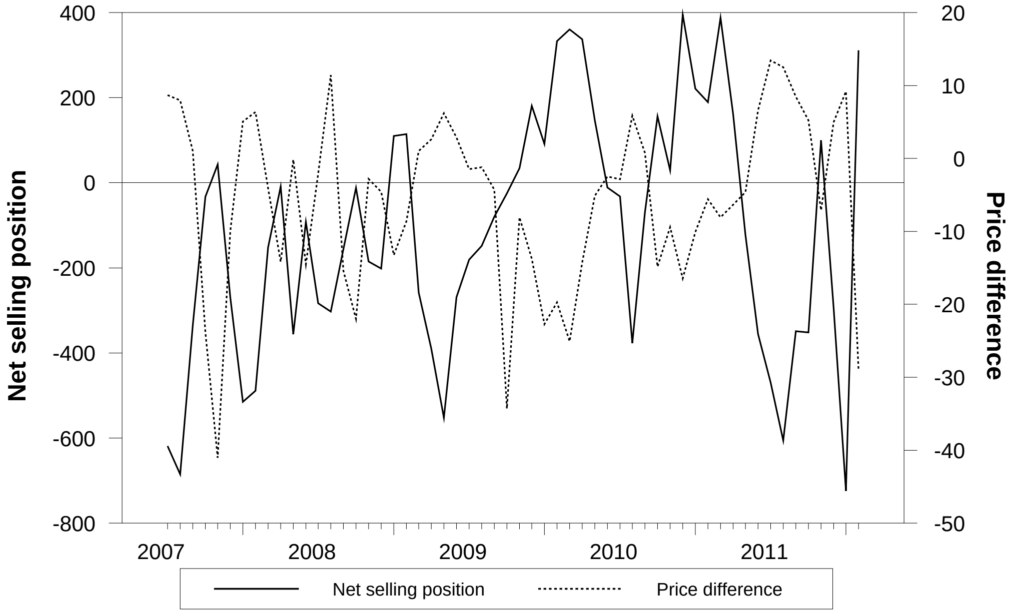


Figure 2: Monthly net trade and price differences. Spain-France



Note that until November 2009 Spain was a net importer of electricity from France and net exporter of electricity to Portugal. After that period there was a sharp increase in the use of generation from renewable sources in Spain. Thereafter, the net selling position with Portugal has shrunk and it has turned negative. Variability has also sharply increased in both interfaces.

The degree of utilization observed at the interface between the two areas of MIBEL has historically been high, and the entry into force of the market splitting mechanism has allowed almost full occupation. Even when the level of occupation of the lines connecting the two countries is satisfactory, this is a fact to be relativized in terms of total value capacity available for commercial purposes. The proportion of hours with congestion is 34.5 percent, of which 32 percent result in a lower price on the Spanish market than on the Portuguese one. This highlights the fact that despite this being one of the European interconnections in which the share of total consumption has increased most rapidly, congestion is still significant. The expectation is to reach an available capacity in 2014 of close to 3000 MW either way, which should enable the degree of structural congestion to be reduced significantly.

The correlation between the net selling position of Spain with respect to each trading partner and the differences in the system marginal prices is 0.7348 with respect to France and 0.7237 with respect to Portugal. However, although correlation is close to constant for the whole sample period between France and Spain, for Portugal and Spain it is more volatile. As the price difference between Spain and either trading partner increases there is an increase in the net selling position. Thus, the existence of market integration or market interconnection does not significantly affect correlation, which is quite high in both cases. Hence, the study of the transmission of volatilities between interconnected markets is justified.

3 Data and Descriptive Statistics

The data used consist of daily electricity prices (measured in €/MWh) from Spain, Portugal and France obtained as the arithmetic mean of the hourly prices for the period from 1-7-2007, the date of the creation of the MIBEL market, to 29-2-2012.[4] Therefore, the sample contains 1705 daily observations for each country. Natural logarithms of the series are taken, with P^S, P^P and P^F being the final price series for Spain, Portugal and France, respectively.

This section describes the main characteristics of the time series distribution and analyzes the stationarity of the series. Figures 3 and 4 show the log of daily electricity prices for each pair of countries, Spain-Portugal and Spain-France, respectively.

Figure 3 shows that the paths of prices in Spain and Portugal are very similar throughout, especially in the second half, when the volatility of the series is also higher. The sample correlation coefficient takes the value 0.97, indicating a very strong positive linear relation between the series. This is because when there is no congestion in the markets the price in both countries is the same.

[4] Results using weighted average prices do not differ from those using simple averages.

Figure 3: Logarithm of electricity prices. Spain-Portugal

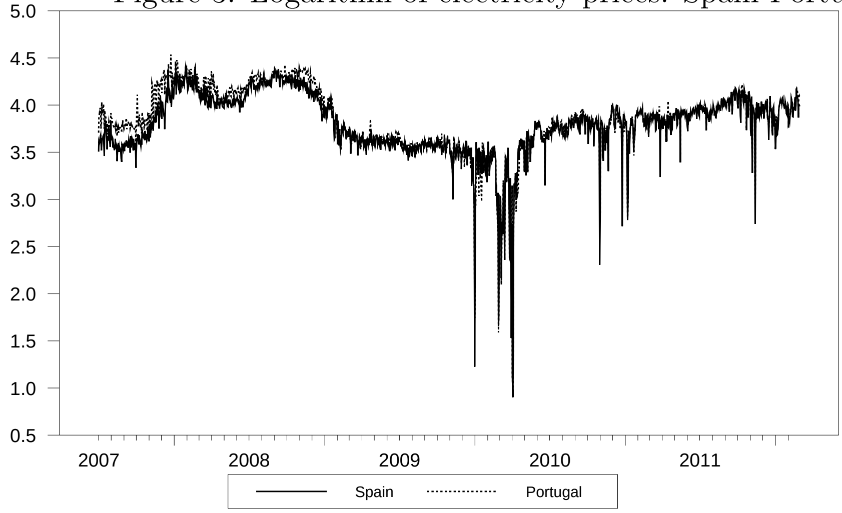
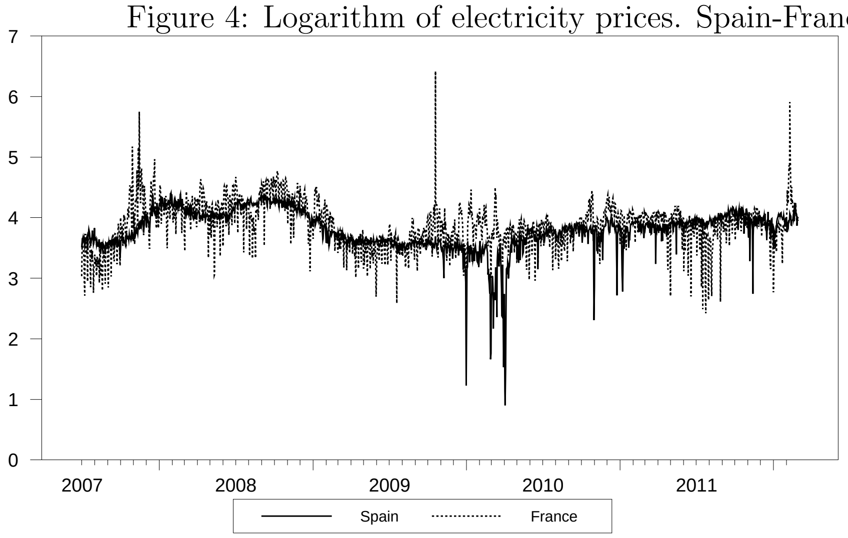


Figure 4: Logarithm of electricity prices. Spain-France



A comparison of the path of the price series in Spain and France, Figure 4, shows that the French series is much more volatile than the Spanish one and differs more than those of Spain and Portugal because the markets are not integrated and hence the prices are never the same. As expected, the sample correlation coefficient is lower: 0.47.

In order to analyze the behavior of the sample correlation over time, a time-varying correlation coefficient is computed via a moving window of 120 observations forming a time series of sample correlation coefficients between the two pairs of electricity price series, shown in Figures 5 and 6. There are some differences in the behavior of the correlation series depending on the pair of countries considered. Specifically, Figure 5 shows that the correlation between prices in Spain and Portugal does not remain constant throughout the sample period: it is higher and more stable in the second half. This is because increasing market interconnection has resulted in a greater number of hours in which the price is the same. However, the correlation coefficients between prices in Spain and France are lower, or even negative, and remain more stable over the sample period. This can be explained by the fact that France is more oriented towards integration through EPEX and Spanish interconnection has not increased significantly.

In general, volatility clusters can be observed in all price series, i.e. periods with high (low) volatility are usually followed by periods with high (low) volatility.

Figure 5: Time-varying sample correlation coefficient. Spain-Portugal

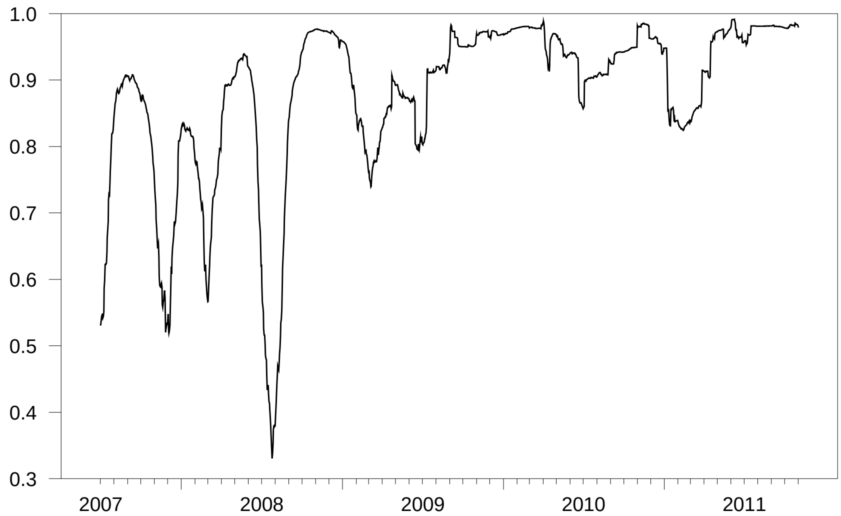


Figure 6: Time-varying sample correlation coefficient. Spain-France

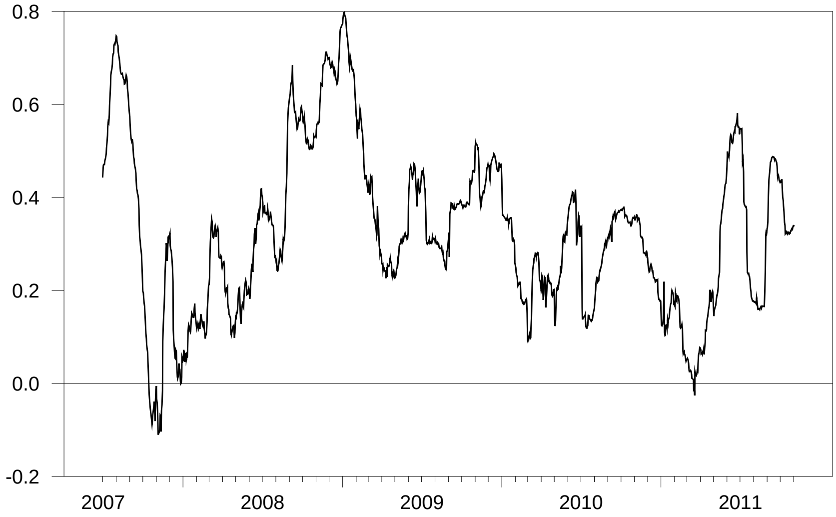


Table 2 reports the main statistics and the results of the ADF unit root tests for the price series and the price series in logarithms. The highest mean price corresponds to the French price series with a value of 52.46 €/MWh, followed by the Portuguese price series, 49.38 €/MWh, and the Spanish one, 46.74 €/MWh. Moreover, prices are more volatile in France, which is reflected in a higher standard deviation. In fact, French prices fluctuate between 11.26 and 612.77 €/MWh, while the minimum price value for both Spanish and Portuguese price series is 2.47 €/MWh and the maximum price is around 90 €/MWh. It should be noted that market rules establish a maximum price of 180.3 €/MWh for MIBEL and 3000 €/MWh for EPEX. There is also a minimum price of 0 €/MWh for MIBEL and -3000 €/MWh for EPEX, which means that negative prices can emerge in equilibrium for some hours. The price series distribution of probability is positively skewed in all three countries at the 10% significance level but leptokurtic in France and platykurtic in Portugal. According to the Jarque-Bera test, there is evidence of a normal distribution of probability in the Spanish series. Regarding the stationarity of the series, the results of the ADF unit root tests when no trend is included in the regressions show that the null hypothesis of unit root is rejected for the French price series at the 1% significance level and also for the Spanish series at the 10% level, while there is evidence of a unit root in the Portuguese price series[5]. Among others, De Vany and Walls (1999a, 1999b), Ferkingstad et al. (2011), Moutinho et al. (2011) and Park et al. (2008) find unit roots in electricity

[5]The ADF tests were also carried out including a trend but results do not change significantly. The number of lags in the ADF regressions was selected according to AIC criterion.

prices or logged prices, while Worthington et al. (2005), Thomas et al. (2011) and Higgs (2009) find stationarity.

When prices are measured in logs, mean, standard deviation, maximum and minimum values do not change qualitatively. However, both Spanish and Portuguese series have a negatively skewed leptokurtic distribution indicating that prices higher than the mean are more probable than those lower than the mean and the tails of the distributions are heavier than those of the normal distribution. In the case of France, the distribution of prices presents excess kurtosis but is not skewed. The distributions of the prices are not normal in the three markets: using the Jarque-Bera test the null hypothesis of normal distribution is rejected for all the series. Finally, all the price series in logarithms are stationary, which is why logarithms are taken in the final price series for estimation purposes.

Table 2: Descriptive statistics and unit root tests of prices and natural logarithms of prices

	Mean	St. Dev.	Max.	Min.	Skew.	Kurt. (Ex.)	J-B	ADF
SP	46.74	13.27	82.13	2.47	0.10^{c}	-0.01	2.89	-2.60^{c}
PO	49.38	14.95	93.35	2.47	0.22^{a}	-0.21^{c}	16.46^{a}	-2.32
FR	52.46	25.31	612.77	11.26	8.62^{a}	161.29^{a}	1869334.42^{a}	-7.15^{a}
SP (Log)	3.80	0.34	4.41	0.90	-2.18^{a}	12.18^{a}	11886.5^{a}	-4.06^{a}
PO (Log)	3.85	0.35	4.54	0.90	-1.81^{a}	9.44^{a}	7261.8^{a}	-3.47^{a}
FR (Log)	3.89	0.37	6.42	2.42	0.07	2.54^{a}	459.3^{a}	-6.02^{a}

a and c indicate rejection of the null hypothesis at 1% and 10% significance levels, respectively. St. Dev. is the standard deviation, Max. the maximum value, Min. the minimum value, Skew. the skewness coefficient, Kurt. (Ex.) the Kurtosis coefficient (in excess), J-B the Jarque-Bera test for non-normality and ADF the Augmented Dickey Fuller test for unit roots. FR-France, SP-Spain and PO-Portugal.

4 Methodology

Various bivariate GARCH models are considered for the MIBEL market on the one hand, and the Spanish and French electricity markets on the other. The mean equation takes the same form in all the models considered:

$$\begin{pmatrix} P_t^S \\ P_t^I \end{pmatrix} = \begin{pmatrix} \alpha_0^S \\ \alpha_0^I \end{pmatrix} + \begin{pmatrix} \alpha_{1S}^S & \alpha_{1I}^S \\ \alpha_{1S}^I & \alpha_{1I}^I \end{pmatrix} \cdot \begin{pmatrix} P_{t-1}^S \\ P_{t-1}^I \end{pmatrix} + \ldots + \begin{pmatrix} \alpha_{JS}^S & \alpha_{JI}^S \\ \alpha_{JS}^I & \alpha_{JI}^I \end{pmatrix} \cdot \begin{pmatrix} P_{t-J}^S \\ P_{t-J}^I \end{pmatrix}$$

$$+\begin{pmatrix} \delta_0^S & 0 \\ 0 & \delta_0^I \end{pmatrix} \cdot \begin{pmatrix} W_t^S \\ W_t^I \end{pmatrix} + \begin{pmatrix} \delta_1^S & \delta_2^S & \dots & \delta_{11}^S \\ \delta_1^I & \delta_2^I & \dots & \delta_{11}^I \end{pmatrix} \cdot \begin{pmatrix} JAN_t \\ FEB_t \\ MAR_t \\ \vdots \\ NOV_t \end{pmatrix} + \begin{pmatrix} \epsilon_t^S \\ \epsilon_t^I \end{pmatrix}, \quad (1)$$

where $t = 1, \dots, 1705$, S stands for Spain and $I = P$, F for Portugal and France. $(W_t^S\ W_t^I)'$ is a vector of dummy variables for weekends and holidays in Spain and Portugal or France, respectively, and $(JAN_t\ FEB_t\ \dots NOV_t)'$ is a vector of monthly dummy variables. The optimal number of lags, J, is such that errors are white noise and the figure differs depending on the pair of countries considered. It should be noted that the main difference with respect to financial series is that electricity price series present an important serial correlation so that the number of lags needed to get uncorrelated errors is large. Finally, $\epsilon_t = (\epsilon_t^S\ \epsilon_t^I)' = \mu_t H_t^{1/2}$ is a bivariate vector, where μ_t is an *i.i.d.* normally distributed process with mean zero and identity covariance matrix and H_t is the conditional covariance matrix of the price vector $(P_t^S\ P_t^I)'$. These equations show that the electricity price series of each country depends on its own past, the past prices in the other country, weekends and holidays in the own country and the month of the year.

The model is completed with the specification of the conditional covariance matrix, H_t, which can be written as:

$$H_t = \begin{pmatrix} \sigma_{SS,t} & \sigma_{SI,t} \\ \sigma_{IS,t} & \sigma_{II,t} \end{pmatrix} = D_t R_t D_t, \quad (2)$$

where $I = P$, F. R_t is the conditional correlation matrix of ϵ_t and D_t is a diagonal matrix containing the conditional standard deviations of the elements of ϵ_t, that is, $D_t = diag(\sqrt{\sigma_{SS,t}}, \sqrt{\sigma_{II,t}})$. The processes of the standard deviations can be defined as any univariate GARCH model.

To start with, the bivariate constant conditional correlation (CCC) model by Bollerslev (1990) is considered. This model is based on the assumption that the correlation coefficient between the two price series is time-invariant, $\rho_{SI,t} = \rho_{SI}$, $I = P$, F, and therefore $R_t = R$. However, the main drawback of the CCC model is that the assumption of constant conditional correlation may not be true. This hypothesis is tested using the LM statistic proposed by Tse (2000). The dynamic conditional correlation (DCC) model by Engle (2002), in which the conditional correlation is time varying, is also considered. In this model the estimated conditional correlation is continuously computed with the time-varying volatility, which could be closer to reality. To estimate the conditional covariance matrix in (2) the conditional correlation matrix is specified as follows:

$$R_t = diag(q_{SS,t}^{-1/2}, q_{II,t}^{-1/2}) Q_t diag(q_{SS,t}^{-1/2}, q_{II,t}^{-1/2}), \quad I = P, F$$

where the bivariate matrix $Q_t = (q_{SI,t})$ is given by:

$$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} + \theta_1 \mu_{t-1}\mu'_{t-1} + \theta_2 Q_{t-1}, \tag{3}$$

with $\bar{Q}$ being the unconditional covariance matrix of the standardized errors $\mu_{it} = \epsilon_{it}/\sqrt{\sigma_{ii,t}}$.

Estimation of the models requires the specification of the conditional variances of the univariate processes. Three alternatives, from the most general to the most restricted, are considered:

- VARMA(1,1), proposed by Ling and McAleer (2003). The variance terms take the form:

$$\sigma_{ii,t} = w_i + \sum_j a_{ij}\sigma_{jj,t-1} + \sum_j b_{ij}\epsilon^2_{j,t-1}, \tag{4}$$

  where $i, j = S, P$ or $i, j = S, F$, that is, Spain and France or Spain and Portugal, depending on the pair of countries analyzed. This specification is the most general since it captures both own and cross volatility spillovers through the past volatility and the past square error term.

- The following alternative modifies the previous one by not including the cross lagged variance, that is:

$$\sigma_{ii,t} = w_i + a_{ii}\sigma_{ii,t-1} + \sum_j b_{ij}\epsilon^2_{j,t-1}, \tag{5}$$

  where $i, j = S, P$ or $i, j = S, F$. In this specification the cross volatility spillovers are only captured by the past square error term.

- A standard GARCH(1,1):

$$\sigma_{ii,t} = w_i + a_{ii}\sigma_{ii,t-1} + b_{ii}\epsilon^2_{i,t-1}, \tag{6}$$

  where $i = S, P, F$. This specification is the most restricted since it does not consider possible volatility transmissions between different markets. The volatility of a market only depends on the own past volatility and square error term.

The CCC and DCC models with the three different specifications of the variances of the univariate price data series are estimated by maximum likelihood using the BFGS algorithm of optimization.

5 Results

Regarding the estimation results for the MIBEL series, the constant conditional correlation hypothesis assumed in the CCC model is rejected at the 1% significance level using the LM statistic by Tse (2000). This result suggests that models assuming time-varying conditional correlation are more appropriate for the Spanish and Portuguese price series.[6] Table 3 reports the estimation results of the DCC model with the alternative specifications of the univariate variance processes for the MIBEL series. It should be noted that 9 lags are needed in all cases in order to obtain uncorrelated error terms, which means that there is major serial correlation in both series. α^S_{jS} and α^S_{jP}, $j = 1, \ldots, 9$ coefficients measure the mean spillover from Spanish and Portuguese lagged electricity prices, respectively, to the Spanish price. Analogously, α^P_{jS} and α^P_{jP}, $j = 1, \ldots, 9$ coefficients measure the mean spillover from Spanish and Portuguese lagged electricity prices, respectively, to the Portuguese price. In all cases mean spillovers are mostly significant and positive, which means that increases in lagged electricity prices in one country cause an increase in electricity prices in both countries at time t. For example, according to the estimation results in the DCC model with GARCH univariate variances, a 1% increase in the Spanish price causes an increase of 0.57% in the Spanish price the next day and also an increase of 0.12% in the Portuguese price the next day. However, some significant coefficients are negative, specifically for some even lags, indicating that the relation is inverse. As expected, the magnitude of the mean spillovers is, in general, larger for the price lags in the own country and the most important influence comes from the previous day's lag.

The coefficients of the dummy variables for weekends and holidays, δ^S_0 and δ^P_0, are significant and negative. This is the result of significant reduction of demand for electricity coming from industrial users on those dates. Monthly dummy variables were included as regressors in the mean equations. However, those that were not significant at the 10% level, either individually or jointly, have been removed. Some monthly effects are significant but results are different depending on the dependent variable in the mean equation, P^S_t or P^P_t, and the specification considered. All the models estimate that prices in March are lower than in any other month in Spain. However, for Portugal there is no clear pattern and results differ depending on the model.

Regarding the estimation results of the variance equation, in the DCC model with a VARMA process for the univariate variances, a_{SP} and a_{PS} coefficients, which measure the GARCH spillovers from the Portuguese market to Spanish volatility and vice versa, respectively, are not significant at the 5% level. This means that there are no GARCH volatility spillovers between Spanish and Portuguese prices: the only GARCH volatility shocks that affect the price in a market

[6] Estimation results of the CCC model do not change significantly across the three specifications for the univariate variance processes, equations (4), (5) and (6), and are available from the authors upon request.

Table 3: Estimated coefficients. Spain-Portugal

Coeff.	DCC-A	DCC-B	DCC-C	Coeff	DCC-A	DCC-B	DCC-C
α_0^S	0.024	0.021	0.030	α_0^P	0.039^{b}	0.003	0.003
α_{1S}^S	0.577^{a}	0.570^{a}	0.568^{a}	α_{1S}^P	0.110^{a}	0.120^{a}	0.124^{a}
α_{2S}^S	0.048^{a}	0.048^{b}	0.041^{a}	α_{2S}^P	-0.024^{a}	-0.035	-0.041^{a}
α_{3S}^S	0.128^{a}	0.139^{a}	0.083^{a}	α_{3S}^P	0.055^{a}	0.067^{a}	0.022^{a}
α_{4S}^S	-0.069^{a}	-0.076^{a}	-0.003	α_{4S}^P	-0.091^{a}	-0.108^{a}	-0.035^{a}
α_{5S}^S	0.114^{a}	0.157^{a}	0.080^{a}	α_{5S}^P	0.069^{a}	0.099^{a}	0.039^{a}
α_{6S}^S	0.043^{a}	0.022	0.078^{a}	α_{6S}^P	-0.070^{a}	-0.087^{a}	-0.043^{a}
α_{7S}^S	0.216^{a}	0.200^{a}	0.178^{a}	α_{7S}^P	0.010^{a}	0.092^{a}	0.065^{a}
α_{8S}^S	-0.159^{a}	-0.143^{a}	-0.122^{a}	α_{8S}^P	-0.103^{a}	-0.102^{a}	-0.082^{a}
α_{9S}^S	0.068^{a}	0.067^{a}	0.070^{a}	α_{9S}^P	0.003	0.011	0.001
α_{1P}^S	0.074^{a}	0.060^{b}	0.044^{a}	α_{1P}^P	0.463^{a}	0.451^{a}	0.442^{a}
α_{2P}^S	-0.056^{b}	-0.061^{a}	-0.027^{a}	α_{2P}^P	0.065^{a}	0.058^{b}	0.081^{a}
α_{3P}^S	-0.020	-0.024	0.013^{a}	α_{3P}^P	0.032^{a}	0.031^{b}	0.060^{a}
α_{4P}^S	0.064^{a}	0.081^{a}	0.028^{a}	α_{4P}^P	0.106^{a}	0.138^{a}	0.086^{a}
α_{5P}^S	-0.045^{a}	-0.065^{a}	-0.015^{b}	α_{5P}^P	0.008	-0.007	0.021^{a}
α_{6P}^S	-0.006	-0.012	-0.028^{a}	α_{6P}^P	0.137^{a}	0.126^{a}	0.123^{a}
α_{7P}^S	-0.017^{a}	-0.003	0.014^{a}	α_{7P}^P	0.089^{a}	0.103^{a}	0.124^{a}
α_{8P}^S	0.003	0.0002	-0.035^{a}	α_{8P}^P	-0.034	-0.037^{b}	-0.071^{a}
α_{9P}^S	0.035^{a}	0.039^{b}	0.029^{a}	α_{9P}^P	0.080^{a}	0.084^{a}	0.087^{a}
δ_0^S	-0.035^{a}	-0.036^{a}	-0.037^{a}	δ_0^P	-0.039^{a}	-0.039^{a}	-0.040^{a}
δ_1^S	0.012	0.013^{b}	0.014^{b}	δ_1^P	0.009	0.011^{c}	0.012^{c}
δ_3^S	-0.031^{a}	-0.022^{a}	-0.024^{a}	δ_3^P	-0.014^{b}		
δ_5^S		0.010		δ_5^P		0.011^{b}	0.004
				δ_6^P		0.005^{b}	0.005^{a}
δ_{10}^S		0.032^{a}	0.040^{a}	δ_{10}^P	0.020^{a}		0.011^{b}
w_S	0.0003^{a}	0.0003^{a}	0.0003^{a}				
w_P	0.0002^{a}	0.0002^{a}	0.0002^{a}				
a_{SS}	0.724^{a}	0.670^{a}	0.672^{a}				
a_{SP}	-0.066^{c}						
a_{PS}	0.003						
a_{PP}	0.699^{a}	0.703^{a}	0.709^{a}				
b_{SS}	0.254^{a}	0.380^{a}	0.527^{a}				
b_{SP}	0.352^{a}	0.208^{a}					
b_{PS}	0.185^{a}	0.157^{a}					
b_{PP}	0.256^{a}	0.284^{a}	0.406^{a}				
θ_1	0.118^{a}	0.104^{a}	0.093^{a}				
θ_2	0.881^{a}	0.895^{a}	0.906^{a}				
Ln L	4954.73	4946.72	4918.85				
AIC	-9795.46	-9779.44	-9727.70				

a, b and c denote significance at the 1%, 5% and 10% levels, respectively. DCC-A, DCC-B and DCC-C correspond to the DCC model with conditional variances as in equations (4), (5) and (6), respectively.

are those that occur in that same market. However, ARCH effects between the markets are significant and positive, with the effect being larger from Portugal to Spain ($b_{SP} = 0.35$) than from Spain to Portugal ($b_{PS} = 0.19$).

Taking into account that the GARCH spillovers between markets are not significant at the 5% level, it is natural to estimate the DCC model with the specification (5) in which these terms are removed. The results of this estimation show significant positive coefficients. The own ARCH effects are greater than the effects caused in the other market and again ARCH spillovers from the Portuguese market to Spanish volatility are larger than those from the Spanish market to Portuguese volatility. The sum of the estimated coefficients for the conditional correlation equation, $\theta_1 + \theta_2$, is less than one for all DCC models and, therefore, these correlations are mean-reverting.

When the univariate variance processes are specified with a GARCH(1,1), all the coefficients are positive and significant. The estimated coefficients a_{ii} and b_{ii} for $i = S, P$, which represent the own GARCH and ARCH spillovers, respectively, show that the GARCH effects ($a_{SS} = 0.67$ and $a_{PP} = 0.71$) are greater than the ARCH effects ($b_{SS} = 0.53$ and $b_{PP} = 0.41$) in both countries. The sum of the estimated coefficients a_{ii} and b_{ii} for $i = S, P$ is greater than one for both the Spanish and Portuguese electricity price markets, meaning that the processes are not stationary. Higgs (2009) finds similar results for one of the four Australian electricity markets considered in her study.

Table 4 shows that, according to the results of the multivariate version of the Ljung-Box test statistic by Hosking (1980), both the standardized residuals and the squared standardized residuals of the DCC estimated model under GARCH and VARMA specifications of the univariate variances are found not to be autocorrelated at the 1% level, whereas standardized residuals in the model with specification (5) are autocorrelated. Moreover, on the basis of the log-likelihood and the AIC criterion (last two lines in Table 3), the DCC model with the specification of the variances of the univariate processes as a VARMA, equation (4), is the best for representing the behavior of the integrated Spanish and Portuguese electricity prices.

Table 4: Diagnostic tests for standardized residuals.

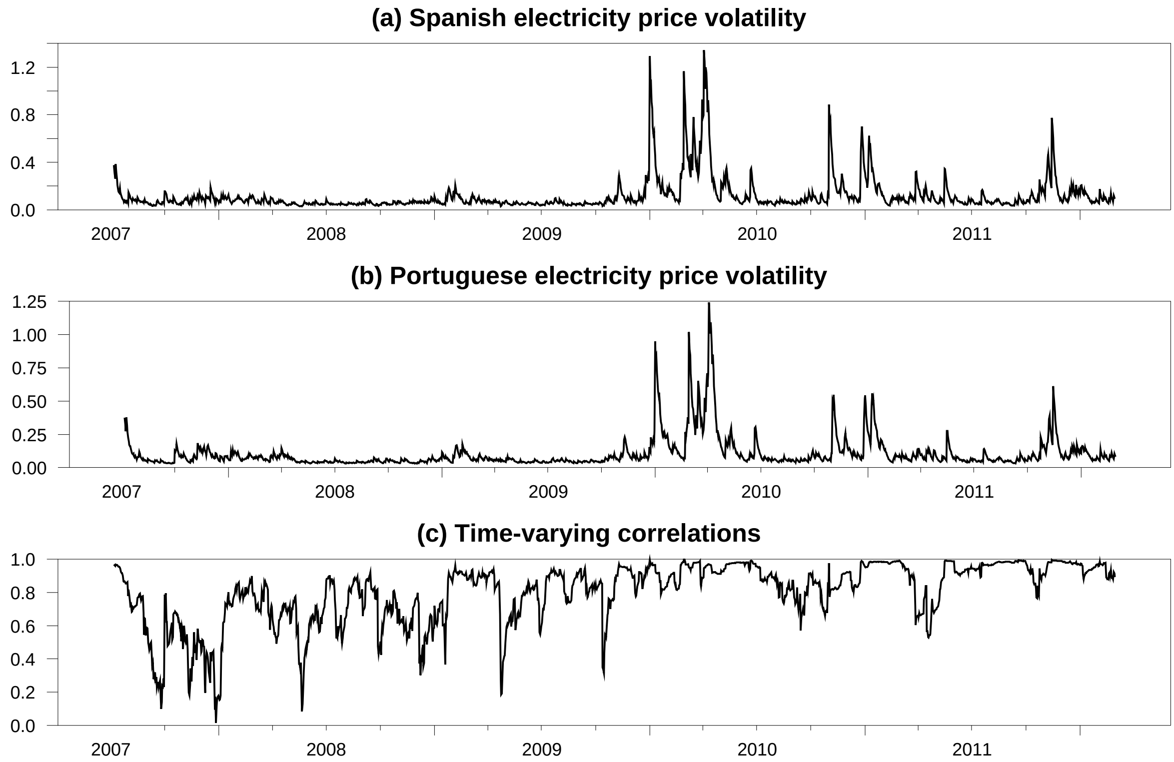
Spain-Portugal			
	DDC-A	DCC-B	DCC-C
Q(8)	48.97	57.29	38.98
p-value	0.03	0.004	0.18
Q(8) sq.	16.58	13.70	14.19
p-value	0.99	0.99	0.99

Q(8) is the value of the multivariate version of the Ljung-Box statistic of order 8 for the standardized residuals and Q(8) sq. is for the squared standardized residuals.

DCC-A, DCC-B and DCC-C correspond to the DCC model with conditional variances as in equations (4), (5) and (6), respectively.

Figure 7 shows the estimated volatility (standard error) for each Spanish and Portuguese price series and time-varying correlations for the DCC model with the VARMA specification for the univariate variances, respectively. The volatility path captures the characteristics of the price series observed in Figure 3, for example, the high volatility in the last part of the sample. The estimated correlation mean is 0.8, unevenly distributed and increasing through the sample period, as observed in Figure 5, with the minimum being 0.015 and the maximum 0.997. This result may reflect a growing integration between the Spanish and Portuguese electricity price markets.

Figure 7: Estimated volatility and correlations. DCC-B. Spain-Portugal



The estimation results are very different when the Spanish and French price series are considered. Table 5 reports the estimation results of the CCC and DCC models when a GARCH(1,1) is specified for the univariate variance processes.[7] To start with, the constant conditional correlation hypothesis is not rejected using the Tse (2000) test, with the statistic value being 0.54. This result is expected from Figure 6.[8] The estimated correlation coefficient between price series is 0.12, much smaller than the corresponding sample coefficients. The DCC model, which assumes time-varying correlation, is also estimated in order to compare the results and to detect possible dynamics in correlations in response to innovations that are

[7]Specifications (4) and (5) were also considered but convergence was not reached. An extended sample period of the French and Spanish series from January 2002 was also considered in order to analyze the robustness of the estimation results and, although convergence is reached considering specifications (4) and (5), the standardized residuals are correlated.

[8]Although the selection of the window length for computing the time series of sample correlation coefficients is arbitrary, it can give an idea about the path of the correlation.

not captured in the CCC model. The number of lags of price series needed to get uncorrelated standardized residuals is 15, which reflects that Spanish and French prices have a larger dependence on past prices than the Spanish and Portuguese series. In both estimated models own mean spillovers are positive and significant for the first, seventh and fourteenth lags. This reveals that price formation not only depends on the information on the price contained in the previous period but that there is also a strong week effect. Prices at weekends and holidays are significantly lower than the rest of the days, with the figure being higher for the French prices. There are some monthly effects although they differ from one country to the other, reflecting different patterns of consumption. For example, there is evidence of higher prices in January, May and September and lower prices in March in the Spanish market. By contrast, prices are estimated to be lower in February and more significantly in July in the French market.

The estimated mean cross spillovers from Spain to France are, in general, larger than those from France to Spain. The one-lagged mean spillover from Spain to France is positive and significant while the one from France to Spain is not. Overall, it can be observed that the CCC model estimates weak links in the mean price spillovers from France to Spain.

All the coefficients of the variance equation are significant and positive and the magnitudes are very similar in the two models. Both consider that price volatility in a country only depends on the past volatility and innovations in the own market and both ARCH and GARCH effects are larger in the Spanish market than in the French one. Although using the Hosking (1980) test the standardized residuals and their squares in both models are not autocorrelated at the 1% level (see Table 6), according to the log-likelihood and AIC criterion the price series in the electricity markets of Spain and France is better modelled by a CCC model, in which the conditional correlation is assumed to be constant throughout the sample period.

Figure 8 shows the estimated volatility (standard error) for each Spanish and French price series for the CCC model with the GARCH specification for the univariate variances. In both cases, the volatility clusters observed in Figure 4 are captured.

Table 5: Estimated coefficients. Spain-France

Coeff.	CCC-C	DCC-C	Coeff.	CCC-C	DCC-C
α_0^S	0.063^a	0.062^a	α_0^F	0.194^a	0.200^a
α_{1S}^S	0.613^a	0.608^a	α_{1S}^F	0.052^a	0.048^a
α_{2S}^S	0.022	0.037	α_{2S}^F	-0.053^a	-0.048^a
α_{3S}^S	0.069^a	0.051^a	α_{3S}^F	0.062^a	0.058^a
α_{4S}^S	-0.027	-0.016	α_{4S}^F	-0.083^a	-0.090^a
α_{5S}^S	0.118^a	0.109^a	α_{5S}^F	0.049^a	0.054^a
α_{6S}^S	-0.014	0.0002	α_{6S}^F	-0.031	-0.035^a
α_{7S}^S	0.116^a	0.111^a	α_{7S}^F	0.006	0.006
α_{8S}^S	-0.058^a	-0.064^a	α_{8S}^F	-0.073^a	-0.074^a
α_{9S}^S	0.048^b	0.054^a	α_{9S}^F	0.081^a	0.082^a
α_{10S}^S	0.076^a	0.081^a	α_{10S}^F	-0.025	-0.018
α_{11S}^S	0.013	0.009	α_{11S}^F	0.020	0.021^c
α_{12S}^S	0.008	0.009^b	α_{12S}^F	0.015	0.017^c
α_{13S}^S	-0.052^a	-0.051^a	α_{13S}^F	-0.037^b	-0.040^a
α_{14S}^S	0.077^a	0.075^a	α_{14S}^F	0.054^a	0.063^a
α_{15S}^S	-0.058^a	-0.060^a	α_{15S}^F	-0.012	-0.021
α_{1F}^S	-0.005	-0.005	α_{1F}^F	0.644^a	0.646^a
α_{2F}^S	0.012	0.010^a	α_{2F}^F	0.020	0.014
α_{3F}^S	0.012	0.013^a	α_{3F}^F	0.104^a	0.103^a
α_{4F}^S	0.013	0.012^a	α_{4F}^F	0.055^a	0.055^a
α_{5F}^S	0.011	0.012^a	α_{5F}^F	0.079^a	0.080^a
α_{6F}^S	-0.022^a	-0.021^a	α_{6F}^F	-0.009	-0.004
α_{7F}^S	0.036^a	0.036^a	α_{7F}^F	0.259^a	0.252^a
α_{8F}^S	-0.024^b	-0.025^a	α_{8F}^F	-0.261^a	-0.256^a
α_{9F}^S	0.006	0.006^b	α_{9F}^F	-0.032^c	-0.031^c
α_{10F}^S	-0.002	-0.001	α_{10F}^F	-0.002	-0.003
α_{11F}^S	0.001	0.004	α_{11F}^F	0.031^c	0.033^b
α_{12F}^S	0.029^a	0.027^a	α_{12F}^F	0.002	-0.0001
α_{13F}^S	-0.022^b	-0.026^a	α_{13F}^F	-0.020	-0.024^c
α_{14F}^S	0.004	0.006^c	α_{14F}^F	0.195^a	0.196^a
α_{15F}^S	-0.014^c	-0.013^a	α_{15F}^F	-0.126^a	-0.126^a
δ_0^S	-0.048^a	-0.047^a	δ_0^F	-0.147^a	-0.143^a
δ_1^S	0.023^a	0.024^a			
			δ_2^F	-0.026^b	-0.025^b
δ_3^S	-0.021^a	-0.021^a			
δ_5^S	0.013^b	0.014^b	δ_5^F	-0.027	-0.029^c
			δ_7^F	-0.067^a	-0.067^a
δ_9^S	0.012^b	0.011^b			
w_S	0.0003^a	0.0003^a			
w_F	0.004^a	0.004^a			
a_{SS}	0.652^a	0.650^a			
a_{FF}	0.535^a	0.526^a			
b_{SS}	0.492^a	0.483^a			
b_{FF}	0.407^a	0.425^a			
θ_1		0.016^a			
θ_2		0.983^a			
Ln L	2628.90	2623.50			
AIC	-5101.80	-5089.00			

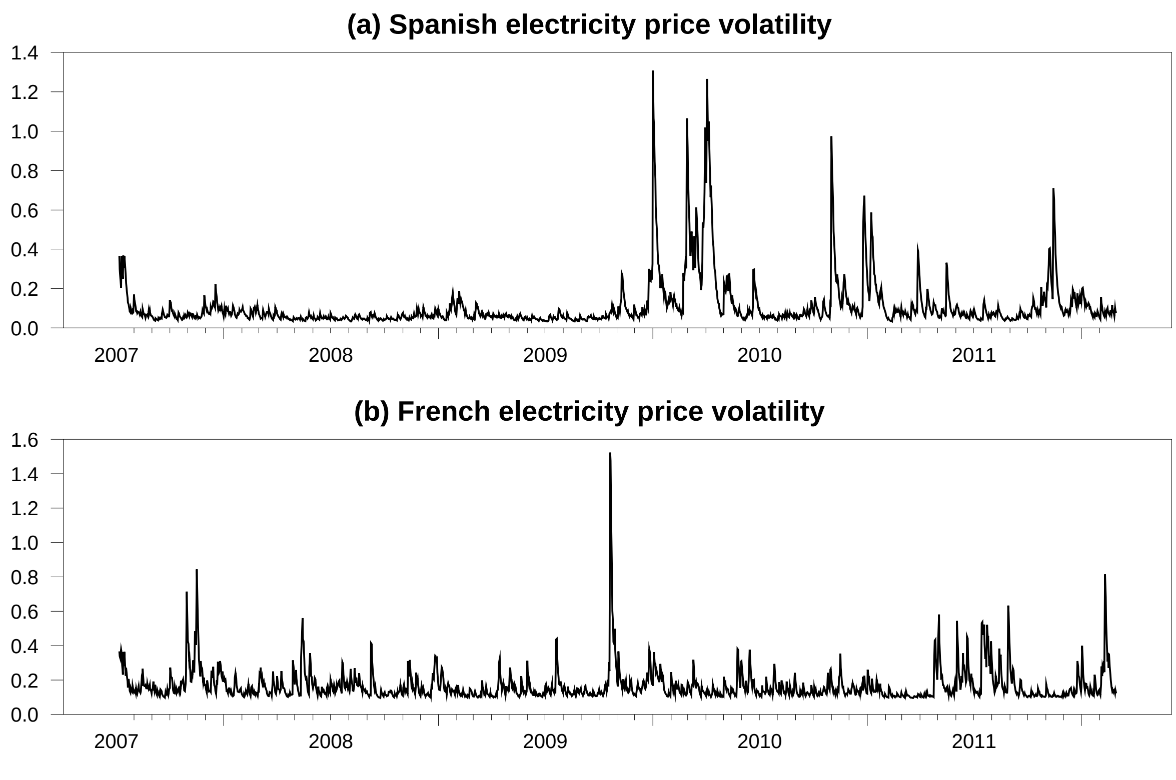
a, *b* and *c* denote significance at the 1%, 5% and 10% levels, respectively.
CCC-C and DCC-C correspond to the CCC and DCC models with conditional variances as in equation (6).

Table 6: Diagnostic tests for standardized residuals.

Spain-France		
	CCC-C	DCC-C
Q(8)	48.83	48.13
p-value	0.03	0.03
Q(8) sq.	13.80	13.84
p-value	0.99	0.99

Q(8) is the value of the multivariate version of the Ljung-Box statistic of order 8 for the standardized residuals and Q(8) sq. is for the squared standardized residuals.
CCC-C and DCC-C correspond to the CCC and DCC models with conditional variances as in equation (6).

Figure 8: Estimated volatility. CCC-C. Spain-France



6 Conclusions

The creation of a fully integrated electricity market in Europe largely depends on harmonization of market rules across countries. Some initial steps have been taken by launching regional initiatives such as MIBEL between Spain and Portugal, and EPEX between France, Germany, Austria and Switzerland. However, lack of sufficient interconnections prevents the ultimate goal of effective price integration from being reached.

Using Spain as the reference country, this paper analyzes the mean price and volatility spillovers within the integrated MIBEL market and between the interconnected Spanish and French markets for the period July 2007 to February 2012. Bivariate CCC and DCC models under three different specifications for the univariate variance processes are estimated and compared. Estimation results show that although weekly and some monthly effects are significant in all markets, there are major differences in the interrelationships between the integrated and interconnected markets analyzed. The DCC model with a VARMA(1,1) for the univariate variance processes is selected to model prices in the MIBEL. In this case there are significant cross mean and volatility spillovers and the estimated time-varying correlation increases throughout the sample period, and has a mean of 0.8. This may imply a process of market integration in terms of price convergence and spillovers which has grown up in recent years and is expected to continue in the future with new interconnections. Therefore, the targets of the Directive 2003/54/CE are being achieved.

By contrast, the models estimated for prices in Spain and France do not enable a similar conclusion to be reached. In fact, the CCC model with a GARCH(1,1) specification for the univariate variance processes fits the joint dynamics of the Spanish and French prices better. The model assumes a fixed correlation for the whole period and its estimated value is 0.12, much lower than the mean estimated correlation for the MIBEL. While the model does not capture the cross volatility spillover effects, the mean cross spillover effects are asymmetric because they are weaker from France to Spain. Although total consumption of electricity in France is greater than in Spain, the value of electricity traded on the Spanish day-ahead market is much higher than that traded in France. This fact helps explain the magnitude of the spillovers. Thus, the evidence of integration between Spanish and French markets is much weaker than that observed in the MIBEL.

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