Price Formation in Electricity Markets

Renata de Abreu Barbosa, Universidad Carlos III de Madrid
Mestre em Economia pela Universidad Carlos III de Madrid. Analista pela CTEEP
renataab@al.insper.edu.br, rebarbosab@cteep.com

Price Formation in Electricity Markets
Two characteristics are a paramount to understand price behaviour in competitive electricity markets: mean reversion and volatility. We have focused our analysis to determine how these characteristics operated in the case of the Spanish wholesale electricity market. We could observe that CCGT play a key role in setting marginal prices as both gas prices and generation present significant price elasticities. In addition, we found that hydropower generation is an important technology to moderate the prices as it is possibly being use as a baseload technology. When analysing volatility aspects, we found that electricity prices exhibit a remarkable structure of time-variant conditional volatility and presented strong weekly seasonality.

Key words: Electricity Price, Power System, Econometric Models.

Formación de Precios en los Mercados de Eletricidad
Dos características son importantes para comprender el comportamiento del precio en mercados competitivos de la electricidad: reversión a la media y volatilidad. Hemos enfocado nuestro análisis en el caso del mercado eléctrico español. Observamos que la tecnología de CCGT (ciclo combinado de gas natural) ejerce un papel dominante en el ajuste de los precios marginales y la elasticidad de precio entre la generación y el precio del gas natural es significante. Además, encontramos que la generación con hydro es una tecnología importante para moderar los precios una vez que es posible utilizarla como tecnología de base. Al analizar aspectos de la volatilidad, encontramos que los precios de la electricidad exhiben una estructura notable de volatilidad condicional variante en el tiempo y estacionalidad semanal fuerte, lo mismo que encontramos en series temporales financieras.

Palabras clave: Precio de la Electricidad, Sistema Eléctrico, Modelos Econométricos

Formação de Preços nos Mercados da Electricidade
Duas características são primordiais para compreender o comportamento dos preços dos mercados competitivos de eletricidade: reversão à média e volatilidade. Focamos nossa análise no estudo de caso do mercado elétrico espanhol. Observamos que a geração que utiliza a tecnologia de Ciclo Combinado de Gás Natural exerce um papel chave na determinação dos preços marginais e é significante a elasticidade-preço entre geração e preço de gás natural. Adicionalmente, vimos que geração hidrelétrica é uma importante tecnologia para moderar os preços de eletricidade uma vez que pode ser utilizada como tecnologia de base. Ao analisar aspectos da volatilidade, encontramos que os preços da eletricidade exibem uma estrutura notável de volatilidade condicional variante no tempo e de forte sazonalidade semanal apresentada, característica comum em séries financeiras.

Palavras- chave: Preço da Eletricidade, Sistema de Energia, Modelos Econométricos

INTRODUCTION

Objective

The objective of this project is to analyze the impact of the mix of generation on the electricity market prices in Spain and to contribute to a better understanding of the fundamental drivers of Spanish power market. For this purpose, a basic understanding of electricity prices, its behaviour and properties are presented.

Relevance

The relevance of this paper is to contribute to a better understanding of the fundamentals and drivers of the electricity market power. The knowledge of these main drivers allows the policy makers to optimize and allocate the mix of energy generation. Furthermore the existence of future energy price market is crucial to understand the tendency of future price to investors.

The methodology of this article could be used to estimate and forecast other commodities prices that present the same structure (mean reversion and high volatility)

Methodology

The price is an endogenous variable. This premise makes it necessary to represent explicitly the expected competitive behavior. There are two methods presented by Hernáez et al[1] that are based on residual demand function. The residual demand represents the potential capacity of a single firm to modify the market price.

The first method is based on a short term competitor´s response, based on historical bidding information. The other method uses historical price information to compute market equilibrium and is a long term analysis.

Once residual demand is estimated, the market can be simulated for different values of own firm´s bids.

Short-term analysis is normally performed by generation companies with an extent of one or two weeks. These studies replace traditional unit commitment studies in which a centralized operator decides the production schedule for every generating unit according to minimum cost and reliability criteria. In a competitive framework, each company has to forecast the part of demand that it wishes to supply as a result of the bidding and clearing process, and plan which units to run for this purpose. This kind of analysis uses the information such as the quantity of hydro resources to be used and the marginal costs of these resources. The result of this analysis is the complete set of offers and bids that should be sent to the market to obtain the previously computed unit commitment. Useful information for subsequent markets, the availability and marginal cost of reserve can be obtained. Furthermore, this provides the basis for short-term price forecasting.

This short-term analysis is based on an estimation of the residual demand and it depends on information available about previous market bids. The marginal cost in this case is closely related to the variable cost of the most expensive unit that has been committed for production by the firm.

Time series clustering techniques and neural networks are some of the alternatives of classification and characterization methodology to deal with historic bidding information.

The second type of method is the medium-term market equilibrium analysis. This analysis deals with a yearly horizon. The capacity of production is determined by decisions including new plant building, seasonal hydro operation and energy sales or fuel purchases. This type of analysis requires an adequate hourly aggregation. One weak point of such method is that it does not reflect the firm´s long-term strategies, because the daily bidding is usually distorted by temporary situations

Limitations

The main limitation of this study is the access of some data: natural gas and coal. As alternative it was used proxies variables to overcome this issue (detail above). Another limitation is to the difficulty to quantify the effect of the price of CO2 on the price in the generation markets. The incidence of the CO2 price in the electrical markets is not clear. This does not means that carbon prices do not affect the electricity market, but it means that CO2 may affect the generation mix but its impact on setting the marginal price is not clear.

Data for wind power generation was not available on daily basis; therefore it was not possible to include it in the analysis.

THE ELECTRICITY MARKET IN SPAIN

The electricity market in Spain was restructured on January, 1998, according to the Electricity Act 54/1997, of November, known as Law of the Electrical Sector. This Law established the legal base to implant an electricity system whose central item was the creation of an electricity wholesaler market.

The liberalization process followed by Spain was not by any means an isolated movement. During the 1990s, a wave of reforms started in the electricity sectors worldwide. From monopolies and implicit regulations, all electricity-related sectors moved to different levels of unbundling, competition and explicit regulation. The paradigm changed: from scale economies and electricity as a “strategic good” to electricity as a commodity and competition. In the case of Spain, the restructuring process followed the liberalization in the UK electricity market and was enacted almost at the same time with liberalization of the electricity market in California (United States).

The centre-piece of the restructuring was a spot market known as “Pool”, in which a day-ahead market is implemented based on an hourly auction process managed by a market operator, through which buyers and sellers submit their bids for each hour of the following day. Power supply has gradually been liberalized, leaving qualified consumers free to participate in day-ahead market.

The Spanish wholesale market is currently organized in a sequence of different types of markets: day-ahead, intra-daily and ancillary services (secondary reserves, tertiary, etc). These markets are managed by two different operators: the market operator and the system operator. OMEL (Operadora del Mercado Español de Electricidad) is the market's wholesale operator and is responsible for its economic management and for the system of electricity sale and purchase, guaranteeing the efficient development of the electricity generation market. Red Eléctrica de España (REE) is the system operator and manages most of the transmission network. It is responsible for the technical management of the Spanish system in order to guarantee electricity supply and proper coordination between the supply and transmission system, as well as the management of international electricity flows. The system's operator and the market operator carry out their duties in coordination.

The purpose of the day-ahead market is the execution of the electricity transactions for a scheduling horizon of the following day, divided into 24 hourly periods. This market operates on a two part model: firstly, once the bidding period has closed the market operation produces the clearance obtaining the hourly prices that will apply for the following day. Secondly, the system operator receives the information and checks for the existence of technical restrictions. Such restriction, as well as changes in the forecasted demand are solved latter with the intra-day market and ancillary services. For the purpose of the present study, we will focus our attention at the outcomes of the day-ahead market.

In the case of the Spanish market, even from the beginning of the liberalization process, the vast majority of the wholesale transactions of energy is realized in the day-ahead market. However, during 2006, it has entered into force a new regulation (Royal Decree Law 3/2006, of 24 of February) which promotes the use of Physical Bilateral Contracts as an alternative to trading in the pool, modifying the mechanism for matching bids for energy submitted simultaneously to the day-ahead and intraday production market by electricity agents belonging to the same business group. Since then, a gradual growth of the use of bilateral contracts has been observed, with a continuous development, in terms of number of participants and liquidity (Capitan & Monroy, 2008).

The analysis of the segment of physical bilateral contracts and day-ahead market by technology reveals a substantially different composition. According the CNE Report (2008) Labout *The Evolution of the Competition in the Gas and Electricity Market*, between 2007 and 2008, the most common generation technologies negotiated in bilateral contracts have been nuclear and coal. On the other hand, in the case of the day-ahead market a diversified composition is observed, that changes over time in relation to the climatologic conditions and in relation to the relative prices of natural gas, coal and carbon emissions, which affect the order of merit of the generation plants.

During the last years, an important increase of the generation of the Special Regime – renewable energy producers and cogeneration - has been registered, determined by the incentive programme launched by the government for the deployment of renewable generation.

On the side of the demand, the Spanish wholesale market has been characterized historically by a significant degree of concentration, and essentially related to the high quota of the main distributors of groups ENDESA and IBERDROLA for the provision of electricity to non-liberalizated customers at a regulated tariff. As a result of the evolution of the liberalization process, the degree of concentration on the demand side is being reduced. Indeed, according to CNE, while in 2006 and 2007 ENDESA and IBERDROLA had a joint quota superior to 60%, in 2008 it has descended to 54% while the quotas of UNION FENOSA, NATURAL GAS and other independent groups have been increased.

In the following sections we present a review on the fundamentals of the electricity market, as well as a review of current alternatives for analysing price behaviour on power markets and lastly, we propose an examination of the structure of the price formation in the Spanish electricity market.

CHARACTERISTICS OF POWER MARKET

Focusing our attention to the price behaviour in liberalizated power markets, two key characteristics are a paramount in the analysis: high volatility and a stronger mean-reverting patterns, and there is a fundamental structural reason for this.

In all literature about electricity and its characteristics, we can find that the crucial feature of the electricity market is its nature. Most spot markets for electricity are defined on hourly intervals (in the case of British market it is half-hourly), and throughout the day, a wide variety of plants will be in action setting the prices at different times. Moreover, we would expect a diversity of plants on the system for at least two reasons. The obvious one is that there exist several energy inputs that can be transformed into electrical energy. The thermal energy contained in fossil fuels can be transformed into electrical energy by the means of the thermodynamics laws. Similar examples can be found in the energy contained in the wind or in the water movement.

The second reason is related to the instantaneous nature of the product: it is a particular commodity with high storage costs. Demand must be instantaneously balanced with supply at every point in time and location over the network.

Furthermore, electricity demand is highly variable over the day and has strong seasonal components. Customers usually are highly inelastic to changes in the electricity prices in the short run and also electricity charges to final consumers typically do not change in real-time as wholesale electricity prices does. This causes that, at periods of low demand, there is excess capacity that increases competition among producers, while at periods of peak demand, agents may face little competition from rivals, and the inelasticity of demand does not deter agents from raising prices.

In addition, consumers use electricity at their convenience and the task of the grid operator is to monitoring this demand process and to call the generators to respond to the fluctuations in demand. Thus, we can say that electricity is produced as a commodity, but is consumed as a service.

The fact that customers use electricity at their conveniences generates seasonality patterns. Such patterns can be traced at different periods of time, namely, yearly, monthly, weekly and/or daily. Demand is affected by climate conditions, like temperature and the number of the daylight hours. Depending on the generation mix, the supply side can also show seasonality – i.e.: hydro plants are dependent on the precipitation, which varies from season to season.

In electricity markets, we can also observe price spikes with very fast mean reversion to the previous price levels. The intuition behind mean reversion is that both high and low electricity prices are temporary, and therefore, prices will tend to maintain an average value over time.

The property of mean reversion can be explained in, at least, two ways. On the one hand, if a shift on demand pushes prices up increasing the incentive of more efficient generators to enter in the market causing a shift in supply at some degree of mean reversion in the evolution of electricity prices (Escribano, Peña, & Villaplana)

On the other hand, since the evolution of weather is a cyclical and mean-reverting process, it could also be argued that prices are mean-reverting because weather conditions are a dominant factor which influences equilibrium prices through changes in demand.

Some related literature

The empirical analysis of both aspects of the electricity prices requires the implementation of econometric techniques that allow us to isolate key components in order to provide evidence on their specific behaviour.

Most provably, mean reverting process is the easiest to analyse – if enough data is available to perform the study – as simple econometric techniques can be employed to observe the underlying pattern that explains the evolution of average prices over time. However, understanding volatility requires the development of more complex alternatives. Several authors have spent a great deal of time developing short-run price forecasting model that captures volatility process in order to enhance their forecasts. Next we review some of the recent studies in this field in order to provide us with tools to analyse volatility in our case study.

To forecast the electricity spot price, the challenge is to develop time-series model that is affluent enough to capture both the nonlinear economic fundamentals and the stochastic behavior induced by imperfect competition.

Despite the large number of analysis about this topic, there is no robust empirical evidence to support one specific model over the rest.

There is a vast type of models founded in the literature and they differ in terms of applied methodology. Serati, Manera and Plotegher (2008) grouped in their paper some available studies in terms of applied methodology: in the group of the autoregressive models we can find the ARMA models (autoregressive moving average), ARX (autoregressive with exogenous variables) and PAR (periodic autoregressive model).

A period autoregressive model (PAR) is one of the new approaches that are currently employed to model electricity prices. It was founded that shocks in the peak periods are larger and less persistent than those in off-peak periods, and they often reappear in the following peak periods. In contrast, shocks in the off peak are smaller, more persistent, and die out during the peak periods. This explains the high correlation between prices within off-peak periods, and their low correlation with prices in peak periods.

Intra-day dynamics are much richer that can be captured by standard models. The PAR model is rich but it´s principal limitation is the large number of parameters that need to be estimated.

One example of PAR model is from the paper of Graeme Guthrie and Steen Videbeck (2007)They analyzed the behavior of the prices in individual trading periods in the New Zealand Electricity Markets between 1966 to 2005 in the half-hourly trading periods (148,944 observations) and divided the prices into five groups: overnight off-peak (24 pm to 7am); morning peak (7 am to 9 am); daytime off-peak (9 am to 5 pm); evening peak (5 pm to 7 pm) and late evening off peak (7 pm to 24 pm).

They find that the prices in different trading periods within each group are highly correlated with each other, yet the correlation between prices in different groups are lower. To understand the correlation structure is of practical importance for the analysis on how generation decisions should be made.

Another different methodology is the called Jump and Regime Switching Models, which have gained high popularity in modeling electricity prices. Switching Models were introduced in econometrics in various different contexts to capture the dynamics of the disruptive spot prices. In the case of an electricity market, a jump in electricity prices can be considered as a change to another regime. The switching mechanism is typically assumed to be governed by a time-homogenous hidden Markov chain with $k \in N$ different possible states representing the k different regimes.

The price behavior can be modeled by, for example, dividing the time series into separate phases or regimes with different underlying processes. We can find in the literature some models: ARJ (autoregressive including Jump), TAR (Threshold Autoregressive) and MS (Markov Switching).

Focusing on models that incorporate stochastic volatility components of heterogeneous durations, Michael Bierbrauer, Stefan Truck, and Rafal Weron (2004) modeled electricity prices with regime switch model. They focused on the properties of spot electricity: seasonality – direct consequence of the fluctuation in demand, due to change in climate conditions, like temperature and the number of daylight hours. The infrequent, but large jumps are caused by extreme load fluctuations (due to severe weather conditions, generation outages, transmission failures, etc) and the mean reversion.

We also can find the volatility models, the so called autoregressive conditional heteroscedasticity (Arch, Engle; 1982) model. The ARCH model relates the error variance to the square of a previous period's error. It is used commonly in modeling series that exhibit high volatility. Besides ARCH, we have the GARCH (Generalized ARCH) and MGARCH (multivariate GARCH) model.

Case Study: The Spanish Power Pool

Since the establishment of the wholesale market in Spain in 1998, few firms have competed. In 2007, the generation market was structured as follows: Endesa (with market share of at about 28%), Iberdrola (24%), Unión Fenosa (12,5%), Gas Natural (6%), Hidrocantábrico (5%), Viesgo (2%); the 19% remaining belongs to other small generators and participants in the special regime for renewable energy and cogeneration (Graeme Guthrie and Steen Videbeck, 2007).

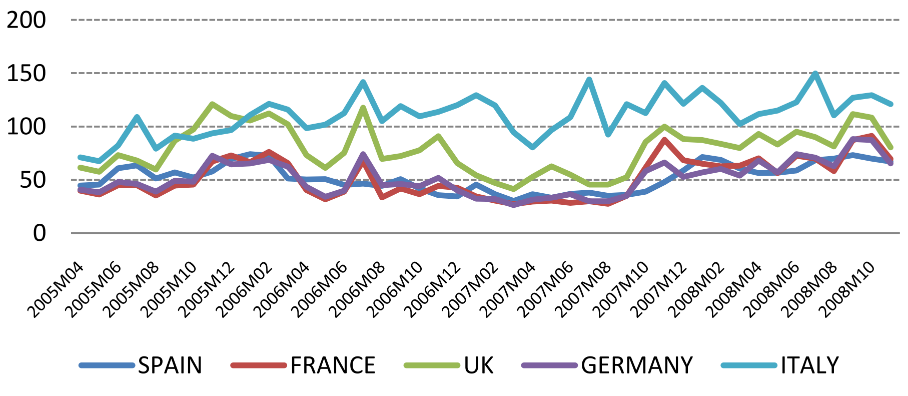
During the period of 2006-2008, a significant growth of the installed capacity has been registered, from 80,544 MW in 2006 to 89,944 MW at the end of 2008. This increase is strongly related to the construction of new Special Regime plants, that has been increased in a 30.4%, from 21,571 MW in 2006 in 28,127 MW in 2008, and, with the entrance in operation of new power stations of combined cycle of gas in the Ordinary Regime, whose capacity has increased in a 4.8% from 58,973 MW in 2006 to 61,817 MW in 2008, according to the CNE monthly report.

The system meets a maximum peak load close to 43,000 MW and a yearly energy demand of about 264,000 GWh in 2008 (Red Eléctrica de España (REE) - Annual Report 2008).

As we focus our research to the day-ahead market, it is important to remind that the mechanism established to obtain hourly prices intends to reproduce a competitive market outcome – as buyers and sellers send simultaneously their bids on a sealed-bid double auction. However, some administrative measures taken during the transition period may affect the incentives of the producers when submitting bids. This is the case of the competition transition charge (Costes de transición a la competencia) which was collected in order to pay the stranded costs of the utilities. Under this charge, electricity companies shall receive during the transition period a fixed payment, expressed in €/kWh, equal to the difference between the average revenues from tariff and the regulated costs.

If we compare the Spanish market with France (POWERNEXT), Italy (PUN), Great Britain (APX-UK) and Germany (EEX), the evolution of the energy prices in each pool are:

Object 1 – Price evolution - €/MWh



The prices in Germany, France, United Kingdom and Spain displayed similar trend. The average price (PUN) on the Italian market is higher than the other markets. A significant differential in prices (17-26 €/MWh) between the Italian Power Exchange and the major foreign exchanges, particularly high in peak hours, was recorded also in 2006.

EEX, Powernext and APX exhibit similar landlords of behavior (elevated volatileness). OMEL and PUN show a more stable behavior in the level of prices with a smaller volatileness.

Empirical analysis

The objective in this section is double: firstly, to understand which are the main drivers in the Spanish wholesale electricity market that cause mean-reverting pattern. For this purpose, we will try to determine how different generating technologies contribute to price formation.

Secondly, we will focus our attention to price volatility and we will try to assess the impact of demand and seasonality patterns in short-run price behaviour in Spain. For that purpose, we propose to develop a short-run price-forecasting model that takes volatility into account.

- Model for the mean-reversion analysis

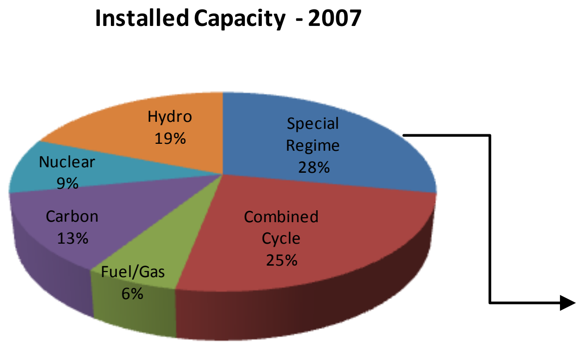
An important aspect to be considered in the discussion is the price effect created by the mix of electricity generation. This section seeks to analyse the impact of different technology of electricity generation on the spot price in Spain.

The Spanish electrical system has a well diversified generation mix. This is a consequence of access to resources, as well as economic and political interests' impulse. In the last decades, the technology of Combined Cycle Gas Turbine (CCGT), thanks to the standardization and modularity of components and to the technological improvements has been able to position itself as the main alternative for fossil fuelled generating plants.

At present, along with the CCGT, the energy of special regime, mainly Wind power, is the one that is undergoing a greater rate of installation in Spain.

The actual mix of generation in Spain is:

Object 2 – Installed Capacity - 2007



Wind	16%
Hydro	2%
Others	2%
No Renewable	8%

Source: REE

As previously explained, the day-ahead market is marginal, and prices are set when supply and demand meet. As demand is highly inelastic in the short-run, it can be assumed that prices are determined by the variable cost of the last generation plant in the merit order. Under this assumption, the variable cost of the marginal technology should have a large impact in the price pattern.

From the economic point of view, the technologies are characterized by different structures from costs and capacity to adapt to changes in demand. Therefore, it becomes efficient to produce using several different technologies at the same time to be able to follow the load curve.

Generation technologies are classified in:

- Baseload: nuclear and coal power stations. They usually have high fixed costs and low variable costs.

Peakload: fuel and gas turbines. They commonly have low fixed costs and high variable costs.

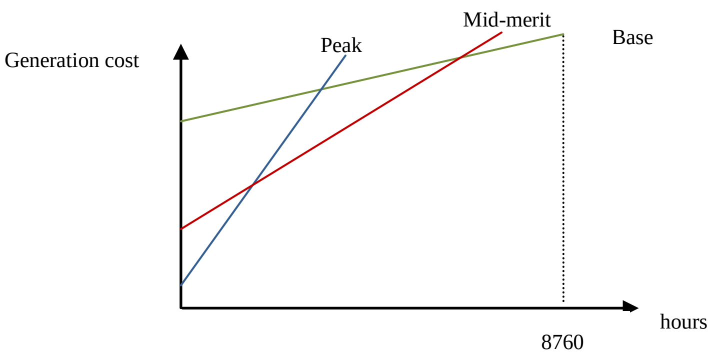
- Peak-and-shoulder: CCGTs and hydro power plants. The costs are somewhere between base and peakload technologies.

Special Regime: wind generators and other renewable generation. They usually present high fix costs and low or null variable cost.

This classification must be considered to be only illustrative as there are specific plants within a technology that can fit in more than one category – this is usually the case of coal and CCGT when carbon prices are included in the economic analysis.

In order to understand the fundamental economics of the capacity mix, we assume a set of costs for *x* technologies, and presume an idealized situation where we can design the optimal capacity mix from these alternatives in order to serve the load duration curve. As described above, knowing the costs, we expect that the nuclear power and wind to be the baseload, and the open cycle gas turbine (OCGT) to be peaking. Coal and CCGTs will be mid merit (in between). Each technology is optimal (minimum total cost) for a certain number of running hours waited to the year, as we can see in the graphic:

Object 3 – Typical formats used for graphics and illustrations



In terms of the stack of the marginal costs or, what is the same, we can see at the supply function an understanding the behaviour of electricity prices. This curve displays the marginal cost of supplying power at a particular level of demand. It is a nonlinear driver of prices. Considering that the demand is highly variable during the day, the translation of this into prices via such a steeply-increasing supply function has an amplification effect in producing the hourly price volatility.

In Spain, the "special regime" (regulated by Royal Decree 661/2007) sets a support scheme for most renewable as well as CHP. The scheme facilitates access to the grid for CHP generators and provides the opportunity to choose between a regulated feed-in-tariff or the spot market price plus a premium. The support is offered in terms of investment grants or advantageous financing for the investment." Status Review of Renewable and Energy Efficiency Support Schemes in EU. CEER 2008

Furthermore, for technical reasons, some types of plant can respond to changes in demand more rapidly than others. For example, a nuclear plant needs to run to a constant load. Other plants, such as a coal plant, can follow the load, but need a long time to start-up and so would not be useful for serving short-duration peaks. There is also a need for quick responsive, generating plant to be available in the load comprising the supply function.

The wind power is non-dispatchable, or 'must run'. It means that is a source of electric power generation that is uncontrollably or more intermittent than conventional power sources. In this case the grid operator is required to take any wind power that is offered. With non-dispatchable wind power entering a grid, there is an economic cost because peak-load and load-following generators operate more often below their optimal efficiency ratings, wind variability causes peak-load diesel and open-cycle gas plants to stop and start more frequently .

In order to analyze the structure of prices, it would be better to use the pool bids as well as the cost of fossil fuels used as inputs (typically, natural gas and coal). The problem is that this information is not fully available: in the case of pool bids, they are not published by the Market Operator; in the case of natural gas and coal, there is no market in Spain that provides spot prices. To overcome this issue, a set of alternatives is proposed:

- Fuel-Oil: Brent
- For natural gas, prices of gas hubs in the Western Europe – such as NBP or Zeebrugge – where employed as a proxy for gas prices in Spain.
- For Coal, the McCloskey coal report for European prices was employed as a proxy for coal prices in Spain.
- Carbon emission prices
- Daily technology-specific generation is employed as a proxy of bids.

With daily average spot electricity prices we estimate a model to see how is the price effect created by the mix of electricity generation and fuel prices. All the series are expressed in €/MWh. The sample period is from April 2005 to November 2008.

Input variables:

The input variables considered are: Brent Index (Oil); NBP and Zeebruge); Coal (McCloskey - ARA Euro Marker) and CO2 emissions (CO2 - EUA Futures Contract). The variables related to generation are: CCGT, hydroelectric, Fuel+gas and other thermoelectric.

Correlations between generation and prices:

Generation	**OMEL**
CCGT	0.52
Hydro	-0.53
Fuel+Gas	0.27
Other Thermal	0.42

Correlations between fuel prices and electricity price:

Prices	**OMEL**
Brent	0.51
Brent (-3m)	0.5
Coal	0.49
CO2	0.79
NBP	0.68
TTF	0.69
ZEE	0.68

Spain presents a strong correlation with the prices of the gas and the CO2 (although this last one can be affected by simultaneity between prices).

Descriptive statistics:

In the next table, we can find the main descriptive statistics for the day-ahead price. We may observe that price series are volatile, have positive skewness and high kurtosis.

Descriptive Statistics	**Spain**
Mean	52.00
Median	50.70
Maximum	94.47
Minimum	21.19
Std. Dev.	14.55
Skewness	0.29
Kurtosis	2.21

Econometric estimation:

The dependent variable is the weighted average of the day-ahead price in the wholesale electricity market and we have two analyzed alternative models:

Lineal model Variables: prices and generation
Model: log-log Variables: prices and generation

There is no significant evidence of differences between the results with linear models and in logarithms. The coefficients of correlation in the models in logarithms are easier to interpret as they represent the elasticity of the independent variable with respect to the price. In addition, side, take logarithms would tend to eliminate right skewness and outliers. In our case right skewness and outliers are explicitly modeled as part of the main sources of uncertainty.

The estimation results:

Object 4 – Typical formats used for graphics and illustrations

Model (a)

Independent Variables	Average price	
	Coef	T-stat
CO2	0.537	4.41
Carbón	0.175	4.28
NBP	0.445	3.45
Gen F+G	0.008	2.36
Gen Hydro	-0.004	-3.48
Constante	27,628	5.66
R^2 Ajustado	0.83	

Model (b)

Independent Variables	ln(Average price)	
	Coef	T-stat
Ln (CO2)	0.056	6.94
Ln (NBP)	0.157	3.5
Ln (CCGT)	0.347	5.29
Ln (F+G)	0.074	3.14
Ln (Hydro)	-0.172	-4.06
Constante	1,299	1.64
R^2 Ajustado	0.87	

The graphics of the independent variables are shown in the annex.

Results from model (b) show that CCGT is the technology that presents the impact on electricity prices; this result is complemented with the evidence obtained from gas prices elasticity. By his flexibility, his relatively short start-up times and their installed capacity in the Spanish system, it is possible to be said that CCGT is the most likely technology to set prices in the wholesale market.

Another interesting outcome is the negative sign in hydropower generation. Due to the high hydroelectric power capacity in Spain, it is possible to presume that "humid" years tend to depress electricity prices as hydropower generation displaces the supply curve to the right.

Lastly, it is interesting to note that Fuel generation has barely any impact on day-ahead prices. This outcome is important as this technology presents high variable costs which in many cases may set the marginal price. The fact that the results show little impact reinforces the previous result of CCGTs being the key technology to explain average prices in the day-ahead market.

a) Volatility model

Here we model the electricity price with a model that account for the volatility, the autoregressive conditional heteroscedasticity (ARCH, Engle (1982)) model. It considers the variance of the current error term to be a function of the variances of the previous time periods' error terms. The ARCH model relates the error variance to the square of a previous period's error. It is employed commonly in modelling time series that exhibit time-varying volatility clustering, i.e. periods of swings followed by periods of relative calm.

The time series analyzed has been constructed as the arithmetic average of the 24 series of hourly system marginal price in €/MWh quoted on the spot market. The data comprises since the liberalization of the sector from January 1998 to June 2009 totalling 4199 observations. The dynamic of the spot (PMD) and the spot log (LPMD) prices and summary statistics is presented in the next graphic and table:

Object 5 – Typical formats used for graphics and illustrations

Statistics	PMD	LPMD
Mean	3.77	1.25
Median	3.52	1.26
Maximum	10.38	2.34
Minimum	0.55	-0.60
Std. Dev.	1.53	0.40
Skewness	0.90	0.05
Kurtosis	3.30	2.63
Jarque-Bera	584.98	26.19
Probability	0.00	0.00
Sum	15,846.53	5,248.13
Sum Sq. Dev.	9,840.90	656.41
Observations	4,199.00	4,199.00

The data admits all the properties which we previously summarized under "stylized facts". Prices range between 0.55 and 10.38 €/MWh. The minimum was reached on December, 31 2002, an official holiday, and the maximum on January, 11 2002. The standard deviation of daily logarithmic price changes equals 40%. The spot prices admit a kurtosis of 3.30 and a skewness of 2.63 implying a right skewed price distribution.

The first step in defining a model for electricity prices consists of finding an appropriate description of the seasonal pattern. The description of the remaining stochastic component is the second critical step.

It must be determined if a transformation of the original series is required in order to deal with the conditions required to perform an ARIMA analysis. Standard ARIMA analysis relies on the assumption that the time series is stationary. A stationary series is one whose statistical properties such as mean, variance, autocorrelation, are all constant over time.

In an empirical framework based on observations of a stochastic processes one of the key elements to consider is if the time series are covariance-stationary or if the data generating processes include an autoregressive unit roots. The choice of the adequate number of autoregressive terms to be included in the auxiliary regression is a key element in this procedure.

Using the well known Augmented Dickey-Fuller test statistic (1979), we found no evidence of unit root in the long run of the daily time series of electricity prices. As we can see in ADF results, the Null Hypothesis that PMD has a unit root can be rejected.

Object 6 – Typical formats used for graphics and illustrations

Augmented Dickey-Fuller test

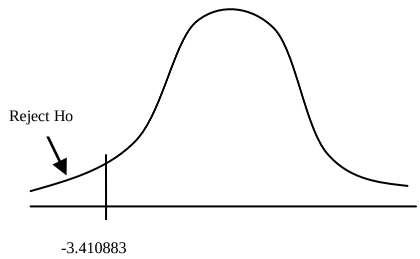
Null Hypothesis: PMD has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 28 (Automatic based on SIC, MAXLAG=30)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.976168	0.0095
Test critical values:	1% level	-3.960239	
	5% level	-3.410883	
	10% level	-3.127244	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(PMD)
Method: Least Squares
Sample (adjusted): 1/30/1998 6/30/2009
Included observations: 4170 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
PMD(-1)	-0.025083	0.006308	-3.976168	0.0001
D(PMD(-1))	-0.357831	0.016362	-21.86937	0.0000
D(PMD(-2))	-0.321023	0.017196	-18.66858	0.0000
D(PMD(-3))	-0.229996	0.01784	-12.89246	0.0000
...	...	...	...	...
D(PMD(-28))	0.110731	0.015434	7.174331	0.0000
C	0.056958	0.018903	3.013115	0.0026
@TREND(1/01/1998)	1.83E-05	7.37E-06	2.484241	0.0130
R-squared	0.481403	Mean dependent var		0.0003
Adjusted R-squared	0.477644	S.D. dependent var		0.5888
S.E. of regression	0.425572	Akaike info criterion		1.1366
Sum squared resid	749.6189	Schwarz criterion		1.1837
Log likelihood	-2338.892	F-statistic		128.0715
Durbin-Watson stat	2.003793	Prob(F-statistic)		0.0000



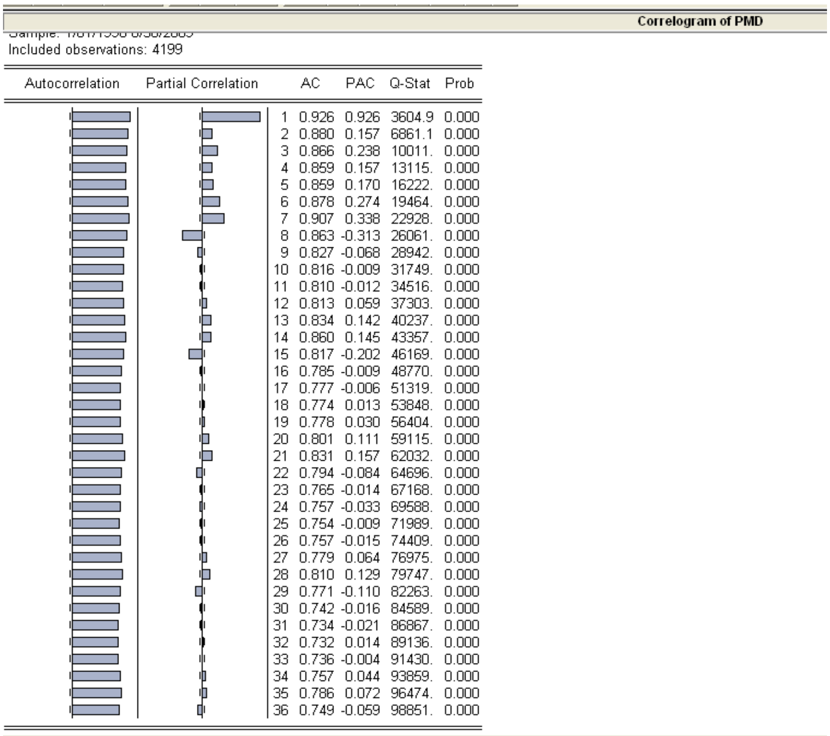
This unit root test, however, says nothing about the stability of the time processes at the seasonal frequencies. So, to identify a seasonal model, the next step will be to determine whether or not a seasonal difference is needed, in addition to or perhaps instead of a non-seasonal difference. We look at time series plots and ACF and the PACF (partial autocorrelation function) of the series, in order to identify the autoregressive (AR) and moving average (MA) parameters of the model and for all possible combinations seasonal difference.

According to the correlogram, the seasonal part of an ARMA model may have an AR factor and an MA factor, and the non-seasonal part of the model may have an autoregressive structure. In the seasonal part of the model, all of these factors operate across multiples of lag “s”, the number of periods in a season.

A seasonal ARMA model is classified as an ARMA (p,q) x (P,Q) model, where P is the number of seasonal autoregressive (SAR) terms and Q is the number of seasonal moving average (SMA) terms.

The correlogram of the ACF/PACF correspond to the variable price. As the first lags show a different pattern with a spike at lag t=1 in the PACF and a irregular or periodical decay in the ACF, so a first or second order autoregressive parameter looks adequate. Many of the other large autocorrelations observed are probably a reflection of the weekly seasonality, so it is necessary to consider the differencing.

Object 7 – Typical formats used for graphics and illustrations



Correlogram of PMD

Included observations: 4199

Lag	AC	PAC	Q-Stat	Prob
1	0.926	0.926	3604.9	0.000
2	0.880	0.157	6861.1	0.000
3	0.866	0.238	10011.	0.000
4	0.859	0.157	13115.	0.000
5	0.859	0.170	16222.	0.000
6	0.878	0.274	19464.	0.000
7	0.907	0.338	22928.	0.000
8	0.863	-0.313	26061.	0.000
9	0.827	-0.068	28942.	0.000
10	0.816	-0.009	31749.	0.000
11	0.810	-0.012	34516.	0.000
12	0.813	0.059	37303.	0.000
13	0.834	0.142	40237.	0.000
14	0.860	0.145	43357.	0.000
15	0.817	-0.202	46169.	0.000
16	0.785	-0.009	48770.	0.000
17	0.777	-0.006	51319.	0.000
18	0.774	0.013	53848.	0.000
19	0.778	0.030	56404.	0.000
20	0.801	0.111	59115.	0.000
21	0.831	0.157	62032.	0.000
22	0.794	-0.084	64696.	0.000
23	0.765	-0.014	67168.	0.000
24	0.757	-0.033	69588.	0.000
25	0.754	-0.009	71989.	0.000
26	0.757	-0.015	74409.	0.000
27	0.779	0.064	76975.	0.000
28	0.810	0.129	79747.	0.000
29	0.771	-0.110	82263.	0.000
30	0.742	-0.016	84589.	0.000
31	0.734	-0.021	86867.	0.000
32	0.732	0.014	89136.	0.000
33	0.736	-0.004	91430.	0.000
34	0.757	0.044	93859.	0.000
35	0.786	0.072	96474.	0.000
36	0.749	-0.059	98851.	0.000

Following Escribano (2002), as we are dealing with equilibrium electricity prices, we have decided not to take logarithms since this transformation would tend to eliminate right skewness and outliers. As in his paper, here right skewness and outliers are also explicitly modelled as part of the main sources of uncertainty.

During the identification procedure the principle of parsimony is applied. According to this principle, models with as few coefficients as necessary to adequately explain the behaviour of the data will be selected.

Electricity price exhibit a remarkable structure of time-variant conditional volatility. It can be fitted by autoregressive conditional heteroskedasticity ARCH (Autoregressive Conditional Heteroskedasticity) models.

ARCH models are specifically designed to model and forecast conditional variances. The variance of the dependent variable is modelled as a function of past values of the dependent variable and independent, or exogenous variables. In developing an ARCH model, two distinct specifications must be provided: one for the conditional mean and one for the conditional variance.

Often interpreted in a financial context, where an agent or trader predicts this period's variance by forming a weighted average of a long term average (the constant), the forecasted variance from last period (the GARCH term), and information about volatility observed in the previous period (the ARCH term). An ordinary ARCH model is a special case of a GARCH specification in which there are no lagged forecast variances in the conditional variance equation-i.e., a GARCH(0, 1).

The best model for the volatility was a GARCH (1,1). ARCH models are typically estimated by the method of maximum likelihood. The “(1, 1)” in GARCH(1, 1) refers to the presence of a first-order autoregressive GARCH term (the first term in parentheses) and a first-order moving average ARCH term (the second term in parentheses).

The results are:

Object 8 – Typical formats used for graphics and illustrations

Dependent Variable: Price

Method: ML - ARCH (Marquardt) - Normal distribution

Mean Equation:	Coefficient	Std. Error
C	34.6127	6.2937
DUMMY2	28.5518	4.6697
AR(1)	0.6163	0.0155
AR(2)	0.3254	0.0165
SAR(7)	0.9861	0.0022
MA(2)	-0.2866	0.0191
SMA(7)	-0.8687	0.0085
Variance Equation:		
C	0.19883	0.02204
RESID(-1)^2	0.09043	0.00522
GARCH(-1)	0.90232	0.00484
R-squared	0.92367	
Adjusted R-squared	0.92351	

The output from ARCH estimation is divided into two sections: the upper part provides the standard output for the “mean equation” and the lower part, “Variance Equation”.

For the “mean equation”, the best model chosen was an ARMA (2, 2) and a seasonal ARMA (7, 7). We create two dummies for the days of maximum and minimum price: the minimum was reached on December 31 2002, and the maximum on January 11 2002. The significant dummy was for the maximum price (DUMMY2). The ARMA model is appropriate in this type of system which is a function of a series of unobserved shocks (the Moving Average part) as well as its own behaviour (the Autoregressive part). Results from the model show that the price series tend to follow a weekly seasonal pattern which may represent that demand follows a similar load curve over the weeks.

The lower part, “Variance Equation” contains the coefficients and standard errors for the coefficients of the variance equation. The ARCH parameters correspond to “RESID^2”, called α and the GARCH parameters to GARCH(-1), called β. As we can observe from the results the sum of the ARCH and GARCH coefficient (α+β) is very close to one, indicating that volatility shocks are quite persistent.

Once a tentative model is specified, it is obligatory to check if the residuals are normally distributed. There are varieties of test that can be done to accomplish this task: histogram of the residuals, the ACF and PACF of the residuals, LM serial autocorrelation test, etc. From the test of the residuals (showed in the annex), we can conclude that the model adequately captures the stylized facts of the data.

CONCLUSION

The Spanish electrical system has a well diversified generation mix. This is a consequence of access to resources, as well as economic and political interests' impulse. In the last decades, the technology of Combined Cycle Gas Turbine (CCGT), thanks to the standardization and modularity of components and to the technological improvements has been able to position itself as the main alternative for fossil fuelled generating plants. At present, along with the CCGT, the energy of special regime, mainly Wind power, is the one that is undergoing a greater rate of installation in Spain.

Two characteristics are a paramount to understand price behaviour in competitive electricity markets: mean reversion and volatility. We have focused our analysis to determine how these characteristics operated in the case of the Spanish wholesale electricity market.

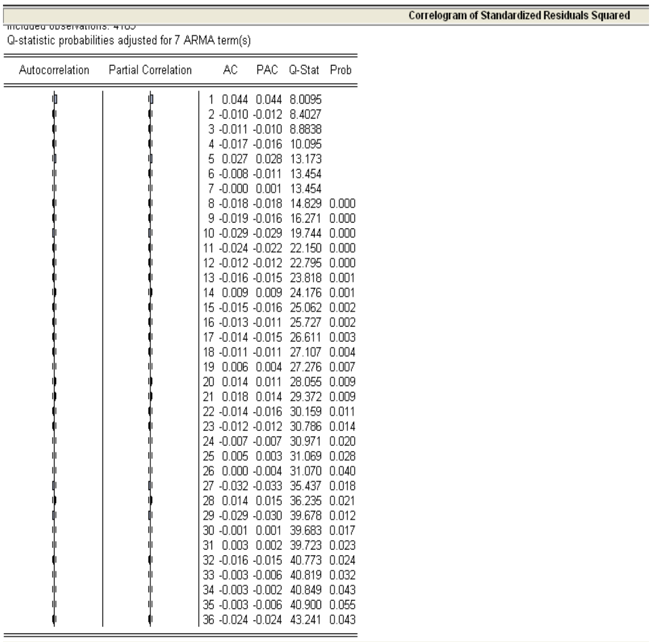
We could observe that CCGT play a key role in setting marginal prices as both gas prices and generation present significant price elasticities. In addition, we found that hydropower generation is an important technology to moderate the prices as it is possibly being use as a baseload technology. When analysing volatility aspects, we found that electricity prices exhibit a remarkable structure of time-variant conditional volatility and presented strong weekly seasonality.

ANNEX

Residual test for the volatility model:

- Correlogram of the residuals:

Object 9 – Typical formats used for graphics and illustrations

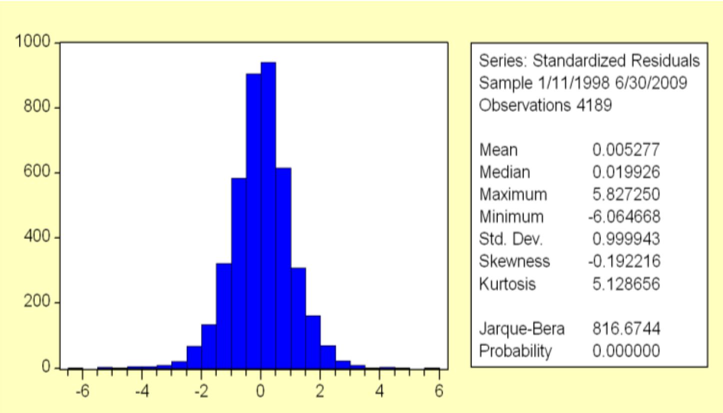


Correlogram of Standardized Residuals Squared

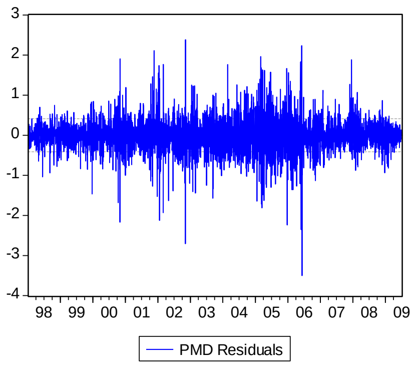
Q-statistic probabilities adjusted for 7 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.044	0.044	8.0095	
		2	-0.010	-0.012	8.4027	
		3	-0.011	-0.010	8.8838	
		4	-0.017	-0.016	10.095	
		5	0.027	0.028	13.173	
		6	-0.008	-0.011	13.454	
		7	-0.000	0.001	13.454	
		8	-0.018	-0.018	14.829	0.000
		9	-0.019	-0.016	16.271	0.000
		10	-0.029	-0.029	19.744	0.000
		11	-0.024	-0.022	22.150	0.000
		12	-0.012	-0.012	22.795	0.000
		13	-0.016	-0.015	23.818	0.001
		14	0.009	0.009	24.176	0.001
		15	-0.015	-0.016	25.062	0.002
		16	-0.013	-0.011	25.727	0.002
		17	-0.014	-0.015	26.611	0.003
		18	-0.011	-0.011	27.107	0.004
		19	0.006	0.004	27.276	0.007
		20	0.014	0.011	28.055	0.009
		21	0.018	0.014	29.372	0.009
		22	-0.014	-0.016	30.159	0.011
		23	-0.012	-0.012	30.786	0.014
		24	-0.007	-0.007	30.971	0.020
		25	0.005	0.003	31.069	0.028
		26	0.000	-0.004	31.070	0.040
		27	-0.032	-0.033	35.437	0.018
		28	0.014	0.015	36.235	0.021
		29	-0.029	-0.030	39.678	0.012
		30	-0.001	0.001	39.683	0.017
		31	0.003	0.002	39.723	0.023
		32	-0.016	-0.015	40.773	0.024
		33	-0.003	-0.006	40.819	0.032
		34	-0.003	-0.002	40.849	0.043
		35	-0.003	-0.006	40.900	0.055
		36	-0.024	-0.024	43.241	0.043

Histogram of the residuals:



Residuals:



ARCH test:

ARCH Test:

F-statistic	8.027018	Probability	0.004631
Obs*R-squared	8.015482	Probability	0.004638

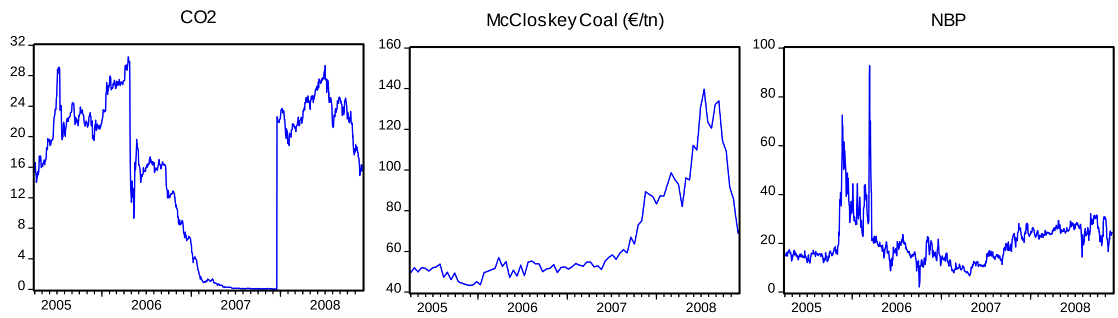
Test Equation:
Dependent Variable: STD_RESID^2
Method: Least Squares
Sample (adjusted): 1/12/1998 6/30/2009
Included observations: 4188 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.956143	0.034948	27.35932	0.0000
STD_RESID^2(-1)	0.043748	0.015441	2.833199	0.0046

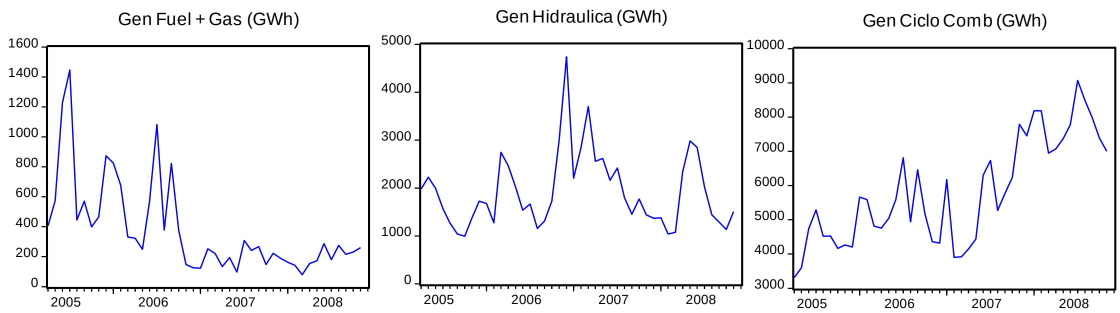
R-squared	0.001914	Mean dependent var	0.999885
Adjusted R-squared	0.001675	S.D. dependent var	2.030663
S.E. of regression	2.028961	Akaike info criterion	4.253402
Sum squared resid	17232.44	Schwarz criterion	4.256430
Log likelihood	-8904.625	F-statistic	8.027018
Durbin-Watson stat	1.998830	Prob(F-statistic)	0.004631

Independent variables

Fuel prices: CO2, Carbón and NBP



Generation: Fuel+gas, Hydro and CCGT:



REFERENCES

Agency, I. E. (2004). *Variability of Wind Power and Other Renewables: Management Options and Strategies* .

Bierbrauer, M., Truck, S., & Weron, R. (2004). *Modeling Electricity Prices with Regime Switching Models.*

Bunn, D. W. *Modelling Prices in Competitive Electricity Markets* .

Capitan, A., & Monroy, C. R. (2008). *Empirical Evaluation of the Efficiency of the Iberian Power Futures Market* .

Cartea, A., & Figueroa, M. G. (2005). *Pricing in Electricity Markets: A Mean Reverting Jump Diffusion Model with Seasonality.*

CNE. (2008). *Informe Sobre la Evolución de la Competencia en los Mercados de Gas y Electricidad.*

de Miera, G. S., González, P. d., & Vizcaíno, I. *Analysing the Impact of Renewable Electricity Support Schemes on Power Prices: The Case of Wind Electricity in Spain* .

Escribano, Á., Peña, J. I., & Villaplana, P. *Modeling Electricity Prices: International Evidence* .

García, C. L. (2002). The Influence of Subsidies on the Production Process: The Case of Wind Energy in Spain . *Electricity* , *15* (4), pp. 79–86.

Guthrie, G., & Videbeck, S. (2007). *Electricity Spot Price Dynamics: Beyond Financial Models.*

Guthrie, G., & Videbeck, S. (2002). *High Frequency Electricity Spot Price Dynamics: An Intra-Day Markets Approach.*

Misiorek, A., Trueck, S., & Weron, R. (2006). *Point and Interval Forecasting of Spot Electricity Prices: Linear vs. Non-Linear Time Series Models.*

Montes, G. M., Martín, E. P.-d., & García, J. O. (2005). *The Current Situation of Wind Energy in Spain.*

Popova, J. (2004). *Spatial Pattern in Modelling Electricity Prices: Evidence From the PJM Market.*

Regulators, C. o. (December 2008). *Status Review of Renewable and Energy Efficiency Support Schemes in EU.*

Sensfuß, F., Ragwitz, M., & Genoese, M. *The Merit-order Effect: A Detailed Analysis of the Price Effect of Renewable Electricity Generation on Spot Market Prices in Germany* .

Serati, M., Manera, M., & Plotegher, M. (2008). *Modelling Electricity Prices: From The State Of The Art To A Draft Of A New Proposal* .

van Kooten, G. C., & Timilsina, G.-d. R. (2009). *Wind Power Development - Economics and Policies.*

Weron, R., Simonsen, I., & Wilman, P. (2003). *Modeling Highly Volatile and Seasonal Markets: Evidence From the Nord Pool Electricity Market.*

Recebido em 03/09/2010
Aprovado em 29/10/2010
Disponibilizado em 03/11/2010
Avaliado pelo sistema *double blind review*