Some stylized facts in electricity markets: a European comparison

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Abstract

Electricity markets are well known for their distinguishing characteristics. Here we analyze and empirically prove some of the stylized facts that have been reported in the literature of spot/base electricity prices/returns, since the construction of a good spot price or derivatives model requires the incorporation of all these stylized facts.

We provide evidence for seasonality, mean reversion, jumps, fat tails, and volatility (estimating a GARCH, a TARCH and an EGARCH volatility models), for 10 European electricity spot markets. The GARCH(1,1) model is the one that seems to better fit the data, at an European level. Before choosing a model for electricity spot prices (and consequently derivatives model) we need to be careful with the market and time span under analysis.

Keywords: Electricity markets, stylized facts, GARCH, EGARCH, TARCH, returns volatility

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1 Introduction

Following the worldwide trend for restructuring public utilities, electricity has emerged as an actively traded commodity in spot, forward and derivatives markets. The most mature markets are those of the UK and NordPool, which started their operation at the beginning of the 1990s, followed shortly by Australasia and towards the end of that decade, by Spain, Germany, the Netherlands and some US states. Electricity prices have developed salient and general characteristics, most notably that of spot volatility, orders of magnitude higher than financial assets and other commodities (Weron, 2005), and of a complex stochastic nature. This pronounced volatility reflects a convolution of economic fundamentals, technical characteristics, agent behavior and aspects of market design, often confounded by environmental constraints and political interventions. A throughout analysis of these various drivers of volatility is clearly crucial to understand the sources of price risk in this commodity, yet unravelling the separate fundamental and behavioral aspects is a challenge that has so far only been partially resolved by researchers.

Since the late 1980's, dramatic changes to the structure of the electricity business have taken place around the world. The original monopolistic situation was replaced by deregulated markets, where consumers in principle were free to choose their provider – the market place for electric power had become competitive. To facilitate trading in these new free markets, exchanges for electric power have been organized. Everything from spot contracts to derivatives, like (standardized, but not marked to market) forward, futures and option contracts, are traded. Bilateral trading has evolved even more dramatically. Apart from spot and forward contracting, large numbers of structured and exotic products are used. The understanding and characterization of the structure of electricity prices is essential in the cornerstone of the risk management and valuation of financial claims and real assets on this commodity.

The main consequence of the deregulation is that electricity prices are determined by the coaction between demand (the agents who buy energy and then sell it to the consumers) and supply (generators) in what is known as a "pool". The result is that the suppliers compete in selling electricity in the pool while agents purchase it from the market pool at prices of equilibrium that are set at a point of intersection of supply and aggregated demand. Across the grid, production and consumption are perfectly synchronized, without any capability for storage. If the two get out of balance, even for a moment, the frequency and voltage of the power fluctuates. The task of the grid operator is to be continuously monitoring the demand process and to call on those generators who have the technical capability and the capacity to respond quickly to the fluctuations in demand.

Electricity markets are complex and characterized by different specificities, like mean-reversion to a long-run level, multi-scale seasonality (intra-day, weekly, seasonal), calendar effects, irregular and fast-reverting spikes as opposed to "smooth" regime-switching, non-normality manifested as positive skewness and leptokurtosis, unstable correlations with fuel prices due to the alternation of marginal plant technologies, and non-storability of electricity[1].

We will try to present, in some detail, a set of statistical facts which emerge from the empirical study of electricity spot prices and which are common to a large set of electricity spot prices and markets throughout the world. As such, they should be viewed as constraints that a stochastic process has to verify in order to reproduce the statistical properties of returns accurately. Unfortunately, currently existing models fail to reproduce all these statistical features at once, showing that they are indeed very constraining. Schwartz (1997) introduces an Ornstein-Uhlenbeck type of model which accounts for the mean reversion of prices and Lucia and Schwartz (2002) extend the range of these models to two-factor models which incorporate a deterministic seasonal component. Cartea and Figueroa (2005) apply a one-factor mean-reverting jump diffusion model for the electricity spot price, adjusted to incorporate seasonality effects and derive the corresponding forward in closed-form to the England and Wales market[2]. Some examples, of authors that also use these models, include Johnson and Barz (1999), Atkins and Chen (2002), Escribano, Peña and Villaplana (2002), Goto and Karolyi (2003), Eydeland and Wolyniec (2003), and Knittel and Roberts (2005).

We will also provide empirical evidence, for a series of ten European countries (Nord Pool, France, Italy, Czech Republic, Poland, Austria, Netherlands, Germany, Spain and United Kingdom), of volatility applying a GARCH, a TARCH and an EGARCH model which are among those mostly applied to volatility estimates. This paper is meant to fill a gap in the literature where we try to provide a comprehensive study, including survey on the way authors have been modelling these stylized facts, and extending empirical analysis to a larger European group of

[1] The non-storability of electricity is likely to affect derivative pricing significantly, notably influencing on the shape of the forward curve and its behavior.

[2] Jump diffusion models the spot price with a constant-time framework featuring a mean-reverting drift, a standard Brownian diffusion process and a Poisson Jump.

countries, and large data spans. The basic idea was to check if we can model in the same way a large set of countries, that are characterized by the same stylized facts. However, we conclude that a model can only be applied if we take into account the market specific characteristics, as well as the time span.

The paper develops as follows: Section 2 describes the data and descriptive statistics; Section 3 analysis the stylized statistical properties of electricity spot prices and provides the literature review; Section 4 presents the empirical models and results achieved; and Section 5 concludes this work.

2 Data and Descriptive Statistics

2.1 Data

The data set employed in this paper gathers 10 European electricity markets. The time span for the considered markets is, for Nord Pool system (NP onwards, which includes Denmark, Finland, Norway and Sweden) from 4 May 1992 to 20 July 2007, for Spain from 1 January 1998 to 29 June 2007, for Holland work days from 26 May 1999 to 5 June 2007, for Holland all days from 17 June 2000 to 14 March 2003, for Germany all days and work days data starts in 16 June 2000 and ends in 31 December 2005 and 5 June 2007, respectively, for UK (United Kingdom) from 27 March 2001 to 25 August 2007, for France from 27 November 2001 to 26 June 2007, for Czech Republic from 1 January 2002 to 19 July 2007, for Poland from 24 June 2002 to 29 June 2007, for Austria from 22 March 2002 to 19 July 2007, and finally for Italy from 1 April 2004 to 30 April 2007.

The electricity price series used in our study were obtained directly from the official websites[3]. As for APX and EEX markets, data was collected from Datastream. The data sets are composed by daily average hourly prices (and half-hourly for UK) of the spot electricity market, and they represent the cost to obtain a certain quantity of electricity in a specific hour (half-hour) of the following day. The time series data for the Netherlands and German electricity markets, were both collected for work days in the week (Monday to Friday, which we will call work days) and for all available days in the week (which we will call week days). These were separated for us to be able to analyze patterns considering/not-considering weekends data[4].

Price for the Nord Pool system is in NOK/MWh, the Spanish electricity market presents hourly electricity prices in cents/kWh, and Poland in PLN/MWh. All other prices are denominated in Euro per Megawatt hour.

2.2 Descriptive statistics

It is well known that in general, financial asset returns are not normally distributed, but they rather exhibit skewness and excess kurtosis. It is no exception with the electricity market, and that's why the context of heavy tails is rather important. Plots of the raw time series of the chosen data sets display, from a first visual inspection, all the stylized facts already mentioned at the introduction, and that will be described in the next section (volatility, mean reversion, seasonality, fat tails and spikes)[5].

Table 1: Descriptive statistics for electricity returns of European countries

[3]We would like to thank Nord Pool and APX Group for providing us with the necessary data for the Nordic countries and United Kingdom, respectively.

[4]See section "stylized facts".

[5]Plots will be provided upon request to the authors.

Country	Mean	Stdev	Skewness	Excess Kurtosis	JB		Observ.
Nord Pool	183,67	102,37	1,38	6,78	5.062,35	(0.000)	5558
Spain	3,45	1,37	1,23	4,81	1.340,08	(0.000)	3467
Holand (work days)	46,18	35,78	6,79	89,75	672.976,30	(0.000)	2095
Holand (all days)	30,23	19,63	4,05	26,26	25.310,52	(0.000)	1001
Germany (work days)	35,90	19,52	4,13	38,22	99.111,08	(0.000)	1818
Germany (all days)	30,80	19,88	4,18	32,04	77.035,26	(0.000)	2025
United Kingdom	24,34	12,71	3,47	26,72	59.631,27	(0.000)	2343
France	34,54	19,72	3,71	33,09	81.545,04	(0.000)	2038
Czech Republic	29,36	13,87	1,29	11,29	6.324,74	(0.000)	2012
Poland	113,38	8,63	-1,40	20,63	24.326,21	(0.000)	1832
Austria	35,90	17,56	2,21	12,65	9.125,26	(0.000)	1945
Italy	62,89	15,79	-0,10	3,18	3,51	(0.173)	1125

Note: The table reports mean, standard deviation, skewness, kurtosis, and the Jarque-Bera (JB) test for normality. The values in parentheses are the p-values.

We apply the classical notion of volatility, taking the standard deviation of the logarithmic price changes

$$R_t = \ln(P_t) - \ln(P_{t-1})$$

where R_t is the return, P_t the electricity price at period t (measured by the daily average of hourly electricity spot prices) and P_{t-1} the electricity price at time t-1, measured at regular intervals of time as an immediate and forward way to measure volatility[6].

The examination of the returns in table 1 indicate that mean returns for all electricity spot markets are positive. The Jarque-Bera statistic indicates that the distribution of returns, for all samples, has fat tails[7] and sharper peaks than the normal distribution. All return series exhibit excess kurtosis, which is consistent with the presence of GARCH effects.

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

There are some markets with tremendous volatility, like Czech Republic, Austria, Italy, France and UK, and significant differences are apparent between the average wholesale electricity prices among the ten markets. The reason for this is attributed to agents learning by Simonsen (2003) and Haldrup and Nielsen (2006). The most volatile markets are the markets for which we have

[6] Volatility for each year was computed as the daily volatility multiplied by the square root of the number of trading days in that given year (in electricity markets we should take into account all days in the year, since trade occurs on Saturdays and Sundays also. So 365 days were considered. However for APXw and EEXw, we have only considered 252 trading days).

[7] Skewed to the right with the exception of Poland and Italy, whose skewness presents negative values, implying that for some days the prices in the respective pools were extremely high for the underlying period.

fewer years of data (the younger markets)[8], and we can see that volatility is high when we consider all week days with respect to only work days in the week[9].

The mix of generation technology has an impact on both the mean and standard deviation of market prices (Wolak, 1998). Prices in the market dominated by fossil fuel or thermal plants technology tend to be much more volatile than the prices in the markets dominated by hydroelectric capacity (Nord Pool and EXAA).

3 Stylized statistical properties of electricity spot prices

In this section we present evidence for a set of stylized statistical facts[10] which are common in the ten European electricity markets analyzed here. Several authors have been reporting some stylized facts relative to electricity price behaviour throughout the years[11]. Hadsell et al. (2004); Knittel and Roberts (2005); Bosco et al. (2006a,2006b); Escribano et al. (2002); Lucia and Schwartz (2002); Carnero et al. (2003); Mugele et al. (2005); Hadsell (2006) are among those authors that report price spikes, seasonality and mean reversion.

For the Nord Pool market, Simonsen (2003) founds that this market is anti-persistent (mean-reverting). Haldrup and Nielsen (2006) discuss seasonality, long memory, and regime switching, volatility clustering, huge jumps and outliers. Weron et al. (2004) report seasonality, mean-reversion and jumps, fitting a jump diffusion and a regime switching model. To capture mean-reversion they use a Vasicek-type stochastic differential equation.

As we can see, before addressing a theoretical model of daily electricity spot prices, taking a look at the price time series gives us a picture of the basic price patterns and a first idea about appropriate modelling approaches. Although most of the mentioned spot price characteristics are already well described by current electricity price models[12], they fail in mapping the complex patterns of electricity prices all at once.

3.1 Seasonality

It is well known that electricity demand exhibits seasonal fluctuations. The major factors that explain the seasonality of electricity prices are business activities and weather conditions. They mostly arise due to changing climate conditions, like temperature and the number of daylight hours. In some markets, and typically those countries that are heavily dependent on hydroelectric generation, such as Norway (where 99% of generation capacity is hydro), Sweden (with roughly 50% hydro), and Austria (69%), supply-side seasonality becomes important: spot prices on the Scandinavian Nord Pool exchange are affected by rainfall and snowmelt. These seasonal fluctuations in demand and supply translate into seasonal behavior of electricity prices, and spot prices in particular[13]. In some markets, however, no clear annual seasonality is present and the spot prices behave similarly throughout the year with spikes occurring in all seasons (examples are Spain, Czech Republic, Poland where most of its spikes are negative, and Italy).

Apart from the annual "sinusoidal" behavior there is a substantial intraday variability. Higher than average prices are observed during the morning and evening peaks, while mid-day and night

[8] Results consistent with the summary statistics by years performed. Results will become available upon request.

[9] For Holland this works in the opposite direction but we need to take into account the time span.

[10] By stylized fact we are considering the properties that are common to a wide range of electricity markets and time periods.

[11] We apologize for not mention all of them here.

[12] See, for example, Schwartz (1997), Pilipovic (1997), Kaminski (1997), Schwartz and Smith (2000), Clewlow and Strickland (2000), Deng (2000), and Lucia and Schwartz (2002)

[13] In sum, electricity prices contain a strong seasonal component, reflecting heating and cooling needs.

prices tend to be lower than average. The intra-week variability, related to the business day-weekend structure, is also nonnegligible. The price begins to increase at roughly 6h a.m., as the populace wakes and the workday begins. This price increase continues throughout the day as demand builds, peaking at 16h. Prices begin to fall thereafter as the workday ends and demand shifts to primarily residential usage.

Higher prices appear from Tuesdays to fridays, with the highest spikes occurring at friday (weekly effects), and around 9 am to 12 am (daily effects). However, prices follow back to normal levels overnight. Cuaresma et al. (2004) report prices higher during weekdays, and intraday patterns and price spikes. The weekday prices are higher than those during the weekends, when major businesses are closed. If we plot realizations of hourly prices over weekly periods, intra-day and weekly seasonal patterns - pronounced early morning and late afternoon demand-driven peaks - with the exception of Sundays, where the morning peak is absent, are evident.

The modeling of intra-week and intraday seasonalities may be approached analogously to modeling annual fluctuations, i.e. by simply taking a sine function of a one week period, or better a sum of sine functions with distinct periods to recover the non-sinusoidal weekly structure. Alternatively, we may apply the moving average technique, which reduces to calculating the average weekly price profile or just extract the mean or median week. Bhanot (2000), Knittel and Roberts (2005) and Lucia and Schwartz (2002) use piecewise constant functions; Cartea and Figueroa (2005) and Pilipovic (1997) model the seasonal pattern by sinusoidal functions; while Stevenson (2001) uses a wavelet decomposition.

Escribano et al. (2002) consider only weekly and monthly seasonality, but take into account volatility periodicity with respect to the 4 seasons of the year. They have also reported mean reversion (slow for NordPool), important price spikes and jumps, and show that electricity prices are mean-reverting with strong volatility (GARCH), and jumps of time-dependent intensity even after adjusting for seasonality. Lucia and Schwartz (2002) using hourly electricity prices from NordPool for the period January 1, 1993 to December 31, 1999, present strong seasonal pattern along the year, strong volatility with seasonal differences, spikes and jumps with extreme values, and strong long memory. They capture mean-reversion and seasonalities but fail to account for the huge and non-negligible observed spikes in the market. Carnero et al. (2003) using hourly electricity prices for APX, NordPool, EEX and Powernext, argue that not only mean and variance of prices depend on the day of the week but also skewness, kurtosis and autocorrelation structure. For NordPool they conclude it shows specific features (the correlation in the squared residuals is present even after taking into account the periodic features of the data), and also long memory features seem to be present in market prices for which they have a long data set. Burger et al. (2004) present a model that simultaneously take into account seasonal patterns, price spikes, mean reversion, price dependent volatilities and long-term non-stationarity.

3.2 Mean-reversion

Energy spot prices are in general regarded to be mean reverting or anti-persistent. The speed of mean reversion, however, depends on several factors including the commodity being analyzed and the delivery provisions associated with the commodity. In electricity markets, it is common to observe sudden price spikes with very fast mean reversion to the previous price levels. In natural gas markets, the mean reversion rate is considerably slower, but the volatilities for longer dated contracts are usually lower than the volatilities for the shorter-dated ones. In oil markets, the mean reversion rate is thought to be longer term, and it can take months, or even years, for prices to revert to their mean (Pindyck, 1999 and Weron, 2005).

Changes in demand push up electricity prices and increase the economic motivation of expensive suppliers to enter the market. So, it is rational to anticipate the evolution of electricity prices to exhibit mean reversion. Alternatively, it is also natural to say that mean reversion is pronounced in the dynamics of electricity prices, because equilibrium prices are highly influenced from the weather through shifts in demand. The evolution of weather is a mean reverting and cyclical process, thus the tendency it has to go back to its mean level will influence the demand and consequently equilibrium prices (Knittel and Roberts, 2005).

The volatility of electricity prices is mostly affected by the presence of sudden and large variations which, typically, last for one day: upward jumps in the price level are usually followed by downward jumps of almost the same size that revert the price to its "normal" level. Price behaviour in the Nord Pool market appears to follow a kind of mean-reverting model with jumps. The mean for which they revert can even change through the years, but prices still come back to the mean level for that specific period.

In order to examine electricity price interdependencies at the European level Bosco et al. (2006b) question the common finding of mean reversion and of no integration of European prices. Estimate a vector error correction model (VECM), and reports the presence of spikes and jumps, heteroskedasticity and strong seasonalities. Hadsell and Shawky (2006) based their study in NYMEX, and report that persistence in volatility is less than 1 in all zones indicating the presence of mean reversion.

3.3 Jumps, spikes and jump clustering

One of the most pronounced features of electricity markets are the abrupt and generally unanticipated extreme changes in the spot prices known as jumps or spikes. Within a very short period of time, the system price can increase substantially and then drop back to the previous level. These temporary price escalations accounts for a large part of the total variation of changes in spot prices and firms that are not prepared to manage the risk arising from price spikes can see their earnings for the whole year evaporate in a few hours. The spike intensity is also non-homogeneous in time. The spikes are especially notorious during on-peak hours[14] on business days, and during high consumption periods: winter in Scandinavia, summer in mid-western U.S., etc. For example, in NP high price spikes occur mostly on winter, when the Nord Pool is surrounded by snow, and since it is highly dependent on hydroelectric power (Weron, 2005). The years of 2003 and 2005 were very important in terms of jump behavior in Europe due to extreme weather conditions.

As the time horizon increases and the data are aggregated the spikes are less and less apparent. For weekly or monthly averages, the effects of price spikes are usually neutralized in the data.

It is not uncommon that prices from one day to the next or even within just a few hours can increase tenfold. The “spiky” nature of spot prices is the effect of non-storability of electricity. Electricity to be delivered at a specific hour cannot be substituted for electricity available shortly after or before. As currently there is no efficient technology (at a reasonable price) for storing vast amounts of power, it has to be consumed at the same time as it is produced. Hence, extreme load fluctuations – caused by severe weather conditions (demand sided shocks) often in combination with generation outages or transmission failures (supply sided shocks)[15] – can lead to price spikes.

[14] On-Peak data corresponds to the average daily price between 7 am and 19 p.m., and Off-Peak data is the daily average price between 00 am to 6 am (6h30m for UK) and 20 p.m. (19h30m for UK) to 24 p.m.. We will work based on "base data" (the average daily price for the 24 hours in the day) in the empirical part of the work. Distinguishing between on-peak and off-peak data is important for derivative contractual terms.

[15] Market mechanism failure and capacity constraints of the network can also cause spikes, because they lead to temporary deviations from perfect competition in the market and therefore to price spikes when temporary monopolists or oligopolists make use of their market power. Because of the physical constraints and the relatively large operating costs of the generators that cannot in a flexible way adjust to the new levels of demand it is also possible to observe negative price spikes.

The spikes are normally quite short-lived, and as soon as the weather phenomenon or outage is over, prices fall back to a normal level (Geman and Roncoroni, 2006; Seifert and Uhrig-Homburg (2006); among others).

Trueck, Weron and Wolff (2007) mention several papers that provide different alternatives on how to identify price spikes, and use EEX to test several methods to detect the spikes. The simplest way to detect outliers is the use of fixed price thresholds (the choice of the levels themselves is non-trivial and rather arbitrary). Conclude that using fixed thresholds without detrending the time series beforehand may lead to an underestimation of spikes at the beginning of the considered period, while for the later years the number of spikes may be overestimated. Recursive filtering techniques are also used, but may lead to an overestimation of the number of extreme returns. To avoid this they apply a variant of a simple moving average based deseasonalilization technique beforehand, to eliminate the weekly component. Instead of using the mean, they use the median, which is more robust to outliers.

Reasons for single, positive or negative, jumps, followed by mean-reverting prices, can be manifold. Power plant or supply line outages can lead to short or long price impacts, depending on the severity and length of the outage. Poisson processes are an easy way to model this jump behavior. Deng (2000), Escribano, Peña and Villaplana (2002), Villaplana (2003) and Cartea and Figueroa (2005) have taken these kind of jumps into account.

Unexpected strong changes in weather can cause price spikes. Spikes are jump patterns which show an initial (positive or negative) jump followed by a reverse directed jump on the next day. As such, the same Poisson models used above are useless. Huisman and Mahieu (2003) models an upward jump followed by a downward jump via regime-switching models. In Barone-Adesi and Gigli (2002), during a jump period, the price is increased by a random percentage over a random time. Geman and Roncoroni (2006) where the first to model jumps and spikes simultaneously, and for this they use a jump direction threshold to force jumps to be negative if the price exceeds the threshold, combined with a seasonal and price depending jump intensity. The only "if" in this type of modelling is the fact that their restriction on positive jumps at normal price levels neglects negative jumps.

Extreme weather situations can also result in very volatile and jumpy price periods due to a high load level. These translate into clusters of jumps in a short time period which can be positive, negative or mixed. Geman and Roncoroni (2006) were able to include this pattern through the deterministic jump intensity. De Jong and Huisman (2002) use a regime-switching model, switching between a mean reversion and a pure jump regime.

Therefore, modelling jumps in electricity prices is crucial to explain observed market data and to account for future price risks. But considering the complex jump patterns identified in electricity markets, the question comes up which jump model can be used.

3.4 Fat tails

Distributions of returns often exhibits "leptokurtosis" meaning that small as well as large upward or downward fluctuations of returns occur more frequently than would be the case under a normal distribution. In particular, their distribution exhibits fat tails.

The value of skewness measures the coefficient of asymmetry of a distribution. If skewness is negative, the data are spread out more to the left of the mean than to the right. The value of kurtosis is a measure of whether the data are peaked or flat relative to a normal distribution. Data sets with high kurtosis tend to have a distinct peak near the mean and have heavy tails[16]. Results

[16] For a normal distribution the skewness and kurtosis are, respectively, 0 and 3. Further, a distribution is normal when the value of JB test equals 0.

from table 1 and histogram plots confirm the non-normal and fat tails behavior of European electricity markets.

To model the process behind the series we have to use correlogram analysis. Autocorrelation (AC) and partial autocorrelation (PAC) functions for R_t show that these series are not white noise, indicating that the electricity spot price is not, for the analyzed periods, a random walk. Lags 7, 14, 21, 28 and 35 are very large. This has been attributed to the fact that the highest part of electricity demand falls abruptly to increase on Mondays (Hadsell et al., 2006; Hadsell, 2006)[17].

Weron (2005) uses mean daily spot (base-load) prices, for the German power exchange (EEX) and Nord Pool, to recover the main characteristics of electricity prices at a daily time scale (spikes, seasonality and mean-reversion). In particular, the extreme volatility and price spikes which lead to heavy-tailed distributions of returns, to conclude that neither the Gaussian, nor the heavy-tailed alternatives yield a reasonable fit. The reason he provides for this is the spurious skewness due to weekly seasonality.

3.5 Volatility

With deregulation and introduction of competition a new challenge has emerged for power market participants. Extreme price volatility, which can be even two orders of magnitude higher than for other commodities or financial instruments, has forced producers and wholesale consumers to hedge not only against volume risk but also against price movements. Price forecasts have become a fundamental input to an energy company's decision-making and strategy development. This in turn has propelled research in energy price modeling and forecasting.

The volatility encountered in electricity markets is exceptional and not comparable with the one observed in other commodity and financial markets. Applying the standard concept of volatility Weron (2005) obtains: for notes and treasury bills less than: 0.5%; stock indices: 1 - 1.5%; commodities like natural gas or crude oil: 1.5 - 4%; very volatile stocks: not more than 4%; and electricity up to 50%.

The high volatility is a pattern due to the transmission and storage problems and of course the requirement of the market to set equilibrium prices in real time. Since it is not easy to correct provisional imbalances of supply and demand in the short-term, the price changes are more extreme in electricity markets than other financial or commodity ones.

Volatility is often viewed as a negative in that it represents uncertainty and risk. However, it can be good in that if one shorts on the peaks, and buys on the lows one can make money, with greater money coming with greater volatility. Due to the non-storability characteristic of electricity, this is however not possible in the spot market. The use of derivatives or block contracts trade was created to diminuish these kind of impacts.

Volatility clustering appears quite evident when we consider entire week days, as opposed to only week work days (Monday to Friday) where volatility is more pronounced and also it presents a more spiky behaviour. Volatility clustering refers to the observation that large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes. A quantitative manifestation of this fact is that, while returns themselves are uncorrelated, absolute returns or their squares display a positive, significant and slowly decaying autocorrelation function. Observations of this type in financial time series have lead to the use of GARCH models in financial forecasting and derivatives pricing. Hadsell et al. (2004) estimate volatility, study time series properties of spot electricity prices, and examine regional

[17] The weekly cycle is one explanation to justify the values presented by the lags multiple of 7. By the AC and PAC plots we were able to see that we are in the presence of a Moving Average model (by AC) and simultaneously in the presence of an Autoregressive model (indicated by PAC). Results will be provided upon request.

differences and similarities, using a sample for the NYMEX market, and a TARCH specification. They conclude there is significant price volatility regardless of region, time differences or stage of deregulation. Knittel and Roberts (2005) investigate the behaviour of California's restructured electricity prices using jump diffusion models and exponential GARCH. They have reported seasons, regular intraday pattern, weekday/weekend cycle, time varying and volatility clustering, mean reversion, and also jumps from every 20 to 33 hours.

Mugele et al. (2005) intended to analyze volatility differences between more and less mature markets, and for this they applied ARMA and GARCH time series with α-stable innovations for modelling the asymmetric, kurtosis and heavy-tailed nature of electricity spot prices (GARCH-in-mean). For the Nordic and German power exchange prices show heavy tails, spikes, high volatility and heteroskedasticity. However, conclude that returns of spot prices in the Polish market can be modelled adequately by the Gaussian distribution[18]. Results suggest the use of heavy-tailed distributions for modelling electricity spot prices.

Hadsell (2006) examines volatility characteristics and the return-volatility-volume relationship in four markets (COB, PV, Cinergy and Entergy) where they present GARCH estimates for electricity futures returns with volume and with lagged volume[19]. They report persistence in volatility, negative skewness and excess kurtosis of returns, and that the asymmetric effect is negative and statistically significant. They also found that innovations are transitory (persistence measure less than one) and that volatility is better explained by prior volatility than by volume for these markets.

The ARCH (Engle, 1982) and GARCH (Bollerslev, 1986) models aim to more accurately describe the phenomenon of volatility clustering and related effects such as kurtosis. The main idea behind these two widely used models is that volatility is dependent upon past realizations of the asset process and related volatility process. This is a more precise formulation of the intuition that asset volatility tends to revert to some mean rather than remaining constant or moving in monotonic fashion over time. Is about this type of models that we will be talking in the next section.

4 Models and Results

4.1 GARCH

The need to capture the time-varying and clustering properties of volatility motivated the Autoregressive Conditional Heteroscedasticity class of models (ARCH) and these are then extended to various directions. Conditional heteroskedasticity is a common property of electricity prices, manifested as periods of high instability followed by periods of relative tranquillity. This volatility clustering implies some predictability, which can be enhanced by modelling asymmetries and non-linearity's in volatility reactions to news.

The regression model with GARCH (p,q) normal errors is defined as

[18] We present evidence for the opposite. A possible explanation may be due to the time span.

[19] Volume/volatility correlation has been identified as a stylized fact of asset returns (Cont, 2001) and proved to be present also in electricity markets by these authors. We will not examine it here, since this is subject of ongoing research.

$$
\begin{aligned}
p_t &= X_t'\beta + \varepsilon_t \\
\varepsilon_t &= \sqrt{h_t}u_t \ , \ u_t|I_{t-1} \sim N(0,1) \\
h_t &= \omega + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} \ , \ a_0 > 0, a_i, \beta_j \geq 0
\end{aligned}
$$

where p_t is the spot price in a specific load period on day t, X_t a vector of exogenous variables, ε_t an i.i.d. serially uncorrelated innovation process and $h_t = Var(\varepsilon_t|I_{t-1}) = E(\varepsilon_t^2|I_{t-1})$, a time varying, positive and measurable function of I_{t-1}, the information set (σ-field) at time $t-1$. Conditional variance is by definition time-varying and a covariance-stationary process under the condition $\sum_{j=1}^{q} a_i + \sum_{j=1}^{p} \beta_j < 1$. The regression model yields a skewed price distribution as it can replicate spikes to some extent. Here we assumed a generalized error distribution for u_t[20].

The time taken for volatility to move halfway back to its unconditional mean following a given deviation, is defined as $(\alpha + \beta)$ in a GARCH specification (where β is a key persistence parameter). With a persistence measure less than one, the number of days it takes volatility to revert half-way back to its mean can be estimated as $\ln(\frac{1}{2})/\ln(\alpha + \beta)$.

Table 2 presents the estimated results for the GARCH(1,1) estimates[21]. The reported values for β are positive, which means that the GARCH effect is positive for this market, and there exists, in general, a high carry-over effect of past to future volatility.

Table 2: GARCH estimates for European electricity returns

GARCH model estimation of volatility

Parameter	NP	OMEL	RC	UK	FR	PL	IT	EXAA	APX	APX1	EEX	EEX1
ω	4.23E-05	0,00	0,01	0,00	0,00	4.39E-05	0,00	0,00	0,00	0,00	0,00	0,00
z-stat.	8,76	5,08	6,40	4,71	3,76	4,35	4,39	3,89	5,64	2,39	5,24	4,13
α	0,34	0,12	0,43	0,22	0,12	0,34	0,22	0,17	0,68	0,29	0,32	0,15
z-stat.	14,68	7,34	7,87	6,49	5,84	6,75	4,29	7,10	7,53	5,20	6,05	8,03
β	0,70	0,84	0,51	0,72	0,85	0,68	0,75	0,83	0,60	0,78	0,64	0,83
z-stat.	46,76	41,53	12,17	19,96	41,78	17,20	20,96	49,49	26,37	24,57	16,75	52,05
Sum sq. resid	13,91	13,98	167,85	13,94	22,97	8,10	6,97	20,50	39,69	23,76	16,19	23,74
DW	2,44	2,09	2,14	2,13	2,02	2,56	2,32	2,31	2,16	1,88	2,11	1,91
α + β	1,03	0,96	0,93	0,94	0,97	1,02	0,97	1,00	1,29	1,07	0,96	0,98
GED param.	1,00	1,24	0,92	1,08	1,05	0,86	0,71	1,02	0,66	0,82	1,01	1,19
z-stat.	81,91	40,60	41,42	49,84	26,49	46,96	32,55	32,93	36,54	26,44	29,30	26,60

Note: GARCH estimates for the daily average base prices (returns), for the ten electricity markets being analyzed here. APX1 and EEX1 stand for APXa and EEXa, respectively. All parameters are statistically significant at a 1% level. APX1 and EEX1 stands for Holland and Germany all available days in the week data and APX and EEX for work days only.

The values of $(\alpha + \beta)$ are greater than 1 for Nord Pool, Poland, Austria and the Netherlands electricity market, which implies non-stationarity in variance. This also implies a mean reverting conditional volatility process in which shocks are permanent in nature. For all the other markets, the value less than one implies a mean reverting conditional volatility process in which shocks

[20] For the reasons underlying this choice, please consult Teräsvirta (2006).

[21] See Silva and Soares (2004) for an approach to a GARCH(1,1) model applied to a MA(8). Here we use in all models an AR(7) representation for returns, which seemed reasonable for almost all countries analysing their PACF and AIC.

are transitory in nature. For the Nord Pool case, this may be due to the fact that it is the oldest market, and since the data set includes several years this may reflect that agents are learning with electricity market behaviors.

4.2 TARCH

As with many other financial time series, the assumption of constant variance over time for the electricity return series is not appropriate. While the GARCH specification captures the conditional variance in the spot returns, periods of high volatility followed by extended periods of relative calm suggest an asymmetric response in electricity prices that is similar to that found in other financial data. The TARCH, or Threshold ARCH specification is one model that handles this type of asymmetry. It also permits estimation of both persistence and mean reversion.

In the TARCH specification we will estimate the following model:

$$\begin{aligned} R_t &= \mu + \varepsilon_t \\ \sigma_t^2 &= \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 d_{t-1} + \beta\sigma_{t-1}^2 \end{aligned}$$

The mean equation expresses spot returns as a random walk process with ε_t, being the error term and the conditional variance σ_t^2, is specified as a function of three terms: the mean ω, the news about volatility from the previous period ε_{t-1}^2 (the ARCH term), and the previous period's forecast variance σ_{t-1}^2 (the GARCH term). The asymmetry in the TARCH model is specified using the parameter $d_t = 1$ if $\varepsilon_t < 0$, and $d_t = 0$ otherwise. In this specification, positive errors, refer to "good news" in the empirical work on equities, and negative errors ("bad news") are expected to have differential effects on the conditional variance ["good news" has an impact of α, while "bad news" has an impact of $\alpha + \gamma$][22].

If $\gamma > 0$, it is said that a leverage effect exists and when $\gamma \neq 0$, the news impact is asymmetric. If the behavior of electricity prices is like other financial time series, then we could expect that γ will be positive, indicating that the occurrence of a negative return will increase volatility more than a positive return of the same size.

The point estimate of persistence, the time taken for volatility to move halfway back to its unconditional mean following a given deviation, is defined by the term $(\alpha + \frac{1}{2}\gamma + \beta)$ in the TARCH model. A value less than one implies a mean reverting conditional volatility process in which shocks are transitory in nature. With a persistence measure less than one, the point estimate of half life (j) in days is $(\alpha + \frac{1}{2}\gamma + \beta)^j = \frac{1}{2}$. This occurs in Spain, Czech Republic, United Kingdom, France and Germany as reported in table 3[23].

Only in the Netherlands market we have positive serial correlation as measured by DW. The positive ARCH term might reflect the effect of a bumpy deregulation process, or even that in all markets participants were learning how electricity markets worked, basing decisions more on prior day returns than on long-run expectations. After all, forming long-run expectations of changing prices were new to market participants, that until recently were regulated. A high value for this parameter α implies an unstable expected volatility, as well as an exaggerated reaction

[22] It should be mentioned that, the "behavior" of "good" and "bad" news in electricity markets behave in opposite direction than that of equities. For equities "good" means $\varepsilon_t > 0$, but for electricity "good" means $\varepsilon_t < 0$. That is, returns that exceed the mean are desirable for equities, but are not for electricity. Given inelastic demand and the non-storability of electricity, when electricity prices exceed the mean, traders may become panicked, as they must purchase electricity at a much higher price. Thus, prices above the mean lead to an asymmetric response (Hadsell et al., 2004).

[23] In table 3 we present the TARCH estimates. Lagged values of R_t were added to the mean equation to correct for autocorrelation as identified by inspection of the Ljung-Box Q-statistics.

by market participants to prior day returns errors. This behavior is likely to generate price extremes. The parameter β measures the impact of the forecasted variance from last period. This indicates a movement of volatility dependence from new information to past volatility. The asymmetric effect, captured by γ, is significantly positive which indicates a strong market response to "positive" news. These conclusions could be taken due to the data spans considered.

Table 3: TARCH estimates for European electricity returns

TARCH model estimation of volatility

Parameter	NP	OMEL	RC	UK	FR	PL	IT	EXAA	APX	APX1	EEX	EEX1
ω	4.47E-05	0,00	0,01	0,00	0,00	4.75E-05	0,00	0,00	0,00	0,00	0,00	0,00
z-stat.	9,43	4,92	8,20	4,80	3,79	4,43	7,36	3,91	7,21	2,40	5,40	4,11
α	0,19	0,07	0,03	0,26	0,07	0,47	1,00	0,14	0,93	0,28	0,28	0,11
z-stat.	8,85	4,47	0,84	7,03	3,42	5,58	3,83	4,61	6,34	4,34	4,38	5,00
γ	0,33	0,08	0,91	-0,19	0,13	-0,18	0,40	0,06	-0,45	0,05	0,09	0,07
z-stat.	7,46	3,20	7,11	-4,43	3,29	-1,83	1,12	1,41	-2,89	0,50	1,13	2,15
β	0,70	0,85	0,46	0,76	0,84	0,66	0,06	0,83	0,55	0,78	0,63	0,83
z-stat.	49,65	44,69	10,54	25,56	43,48	16,39	1,56	49,79	22,80	23,10	16,27	54,10
α+β	0,88	0,92	0,49	1,02	0,92	1,13	1,06	0,97	1,48	1,05	0,91	0,95
α+1/2γ+β	1,05	0,97	0,95	0,93	0,98	1,04	1,26	1,00	1,26	1,08	0,95	0,98
Sum sq. resid	13,86	13,99	169,32	13,94	22,95	8,04	6,99	20,53	39,89	23,75	16,19	23,71
DW	2,43	2,10	2,31	2,14	2,06	2,56	2,34	2,32	2,17	1,88	2,12	1,91
GED param.	1,00	1,24	0,95	1,10	1,06	0,85	0,70	1,02	0,69	0,82	1,01	1,19
z-stat.	83,71	41,14	43,68	42,50	27,00	36,77	25,21	32,97	38,05	26,12	29,24	26,58

Note: TARCH estimates for the ten electricity markets under analysis, based on the returns of the daily average base prices. APX1 and EEX1 stand for APXa and EEXa, respectively. Parameters α and β are statistically significant at 1% except for Italy. Significance of γ can be questioned. APX1 and EEX1 stands for Holland and Germany all available days in the week data and APX and EEX for work days only.

Positive shocks in UK, Poland, Italy and Netherlands exhibited a temporary impact[24], indicating that returns exceeding the mean led to a decrease in conditional volatility that did died down. As such, for the European sample, results are mixed, as opposed to those of Hadsell, Marathe and Shawky (2004).

4.3 EGARCH

The preliminary data analysis revealed that electricity prices exhibit volatility clustering. In addition, intuition tells us that it is also possible that innovations to the price series have an asymmetric impact on the price volatility. A priory, we expect positive price shocks to increase volatility more than negative surprises. The intuition behind this phenomenon is that a positive shock to prices is really an unexpected positive demand shock. Therefore, since marginal costs are convex, positive demand shocks have a larger impact on price changes relative to negative shocks. To test for this effect, we need to specify the price level as the sum of a deterministic component and a stochastic component

$$p_t = \alpha_t + \eta_t$$

where α_t is the mean term. The random term is assumed to follow an autoregressive process

[24]In those with a value greater than one, we have permanent impacts. So, the effects of a positive shock dissipated much more quickly than the effects from a negative shock.

$$\beta(L)\eta_t = \upsilon_t$$

so, $\beta(L)$ is the lag operator. To capture the conditional heteroskedasticity, we adopt the EGARCH model, modeling υ_t as

$$\begin{aligned} \upsilon_t &= \sqrt{h_t}\varepsilon_t \\ \ln(h_t) &= \omega + \sum_{j=1}^{q}\beta_j \ln(h_{t-j}) + \sum_{i=1}^{p}\alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{k=1}^{r}\gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \end{aligned}$$

and ε_t is Gaussian white noise with unit variance. Note that the left-hand side is the log of the conditional variance. This implies that the leverage effect is exponential, rather than quadratic, and that forecasts of the conditional variance are guaranteed to be nonnegative. The presence of leverage effects can be tested by the hypothesis that $\gamma_k < 0$. The impact is asymmetric if $\gamma_i \neq 0$. If γ is greater than 0 and smaller than -1 a positive shock increases variance less than a negative shock. Table 4 presents the estimates.

Nord Pool market obeys the initial prediction that $\gamma < 0$, which means that the effect of negative shocks on the variance of prices is amplified over positive shocks. Results for the reported values of γ are mixed. Some are negative, which is consistent with the hypothesis of leverage effects, but in others, like those of UK, PL, IT, and the Netherlands electricity market, a negative shock increases variance less than a positive.

Table 4: EGARCH estimates for European electricity returns

EGARCH model estimation of volatility

Parameter	NP	OMEL	RC	UK	FR	PL	IT	EXAA	APX	APX1	EEX	EEX1
ω	-0,77	-0,37	-0,42	-0,56	-0,35	-0,60	-3,28	-0,37	-0,67	-0,46	-0,88	-0,37
z-stat.	-16,98	-6,44	-7,63	-6,46	-6,61	-5,61	-7,97	-8,56	-11,83	-5,33	-7,61	-8,25
α	0,47	0,20	0,20	0,26	0,25	0,29	0,80	0,31	0,45	0,40	0,46	0,28
z-stat.	24,18	9,51	5,21	9,89	7,73	7,45	9,31	9,73	13,13	6,72	8,30	9,77
γ	-0,15	-0,06	-0,28	0,12	-0,10	0,13	0,03	-0,02	0,07	0,03	-0,03	-0,04
z-stat.	-10,70	-4,19	-9,50	6,28	-4,40	4,63	0,44	-0,85	2,77	0,67	-0,98	-1,83
β	0,94	0,96	0,92	0,93	0,96	0,94	0,53	0,97	0,92	0,95	0,89	0,97
z-stat.	172,03	115,84	79,19	66,20	109,90	78,73	7,74	150,05	102,19	67,14	46,61	124,22
Sum sq. resid	13,90	13,98	169,09	13,93	22,92	8,06	7,11	20,43	39,82	23,95	16,19	23,72
DW	2,44	2,11	2,29	2,14	2,06	2,56	2,40	2,30	2,17	1,87	2,11	1,92
GED param.	0,99	1,24	0,94	1,12	1,08	0,84	0,70	1,02	0,71	0,82	1,02	1,18
z-stat.	8,20	40,18	43,06	41,98	27,34	46,00	28,18	33,26	42,12	24,26	29,09	27,57

Note: EGARCH estimates for daily average prices (returns), for the ten European electricity markets (countries) under analysis in this work. APX1 and EEX1 stand for APXa and EEXa, respectively. Parameters α and β are statistically significant at 5%. Significance of γ can be questioned. APX1 and EEX1 stands for Holland and Germany all available days in the week data and APX and EEX for work days only.

We have also performed GARCH, TARCH and EGARCH estimates for the 10 electricity markets, estimating these parameters for each of the years under analysis, and considering only subsamples of the datasets available[25]. With these delineations we wanted to measure the components of volatility as markets evolved. After all, because of the newness of electricity

[25] Results are not presented here, but will be provided if requested to the authors.

markets, there is reason to suspect that market participants may require time to learn how to respond to market forces.

In all markets we could not observe clear trends in parameter estimates. Results were inconclusive. In 2001, α was very high, decreasing in 2002 and once more in 2003 (the year where volatility was higher for almost all markets). Maybe this was a transitory year, caused by market rules imposed by EU directives[26], or maybe due to the extreme weather conditions.

This behaviour is likely to generate price extremes. Moreover, when α declines (usually, although less consistent), there was an increase in β, which measures the impact of the forecasted variance for the last period. This indicates a movement of volatility dependence from new information to past volatility. The asymmetric effect, captured by γ, was not always negative or statistically significant. The negative (positive) coefficients indicate a strong market response to "negative news" ("positive news" - $\varepsilon_t > 0$), in a direction that is counter to what is found in other financial time series.

When considering individual years or overall samples, the EGARCH model does not seems a useful alternative, as well as the TARCH model. In this case, the usual GARCH model is the one that fits better.

5 Conclusion

The dynamics of electricity spot price are very complex and quite far from what one usually assumes for financial assets. Mean-reversion, stochastic volatility, seasonalities in annual and weekly periodicity, fat tails and jump behaviors are the joined consequences of the existence of a long term equilibrium price towards which the price is assumed to revert, together with the lack of storage capacities, a rather inelastic demand curve, a marginal cost curve rising sharply and frequent failures in the production or transmission capacities.

Due to these particular features of electricity, spot prices show special characteristics not seen in other commodity markets.

All the present work was developed taking into account a sample of 10 European electricity markets ("pools") daily average base prices, as well as their respective returns, and the usual volatility measure was employed.

We confirm the findings of Knittel and Roberts (2005) since the asymmetric parameter is positive and significant suggesting the presence of an inverse leverage effect[27]. Positive shocks to prices amplify the conditional variance of the process more so than negative shocks, for UK, Poland, Italy and Netherlands. For the other markets under analysis our results contradict those of the authors.

Under the TARCH estimates for the European countries, we have obtained opposite conclusions to those of Hadsell et al. (2004)[28]. Only the most experienced and organized electricity markets see positive shocks having a temporary impact, learning quickly how to adjust these (agents are learning with electricity market behaviour). A good example is the Nord Pool electricity market, that has been deregularized for almost fifteen years ago. So, agents tend to behave differently, since they already include these impacts on prices, smoothing the process, although they react differently to negative impacts (agents are by norm risk averse).

Ideally we should be able to construct a model where we include all the stylized facts reported here at once, and from this provide volatility forecasts in order to conveniently be able to price

[26] Fact to be explored carefully afterwards.

[27] The leverage effect is also a stylized fact of asset returns. By this we mean that most measures of volatility of an asset are negatively correlated with the returns of that asset.

[28] They used a sample of NYMEX market (COB, PV, Cinergy and Entergy), but the opposite results might suggest differences among continents.

electricity derivatives.

Weron et al. (2004) summarize the stylized facts about electricity prices, and review a number of models proposed in the literature. Our work here consists only in presenting and proving some of the stylized facts that have been reported in the literature. Also, we wanted to present the literature that has been trying to model these stylized facts, and to extend the already explored GARCH, TARCH and EGARCH models to a greater number of European countries in order to be able to perform comparative analysis in future work.

Attending the results obtained here, there are a series of stylized facts that can be proved empirically, and a good model should take them into account. However, modelling will depend on the market and time span under analysis. In fact, some of these stylized facts are more pronounced than others, more in some markets than others, and dependent upon the "years" taken into consideration.

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