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Effects of renewables on the stylized facts of electricity prices

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ABSTRACT

Many countries around the world have increased their renewable installed capacity due to a greater awareness of climate concerns. Under this new framework, with renewables being among the main generation sources, the literature warns of a dramatic change in price behaviour. Some of the most commonly claimed effects of having a significant proportion of renewable generating sources in the total electricity production mix include: (i) a systematic decrease in overall wholesale market prices, (ii) a higher occurrence of price jumps, and (iii) a significant increase in price volatility. The goal of the present study is to test whether these changes in price behaviour have actually come about. To do so, we focus on the Spanish day-ahead electricity market as a paradigmatic example. In line with the literature, it is found a statistically negative relationship between the renewable generation share and the day-ahead market marginal prices. As well, we have obtained statistical confirmation of the fact that renewables generation share volatility is transferred to price volatility, though similarly to other generation technologies. Finally, in contrast to the general belief that the introduction of renewable generation would give rise to extreme (positive) prices, according to our results, increases in renewables generation share reduce the probability of upward jumps in prices. The results obtained are of interest for portfolio managers, practitioners and regulators.

Contents

1. Introduction

One of the most generalized actions all over the world to deal with climate change has been the promotion of renewable energy sources. Thus, many countries such as Germany, Spain, USA and China have significantly increased their investment in clean energy sources. Particularly, in Spain, the electricity generated by

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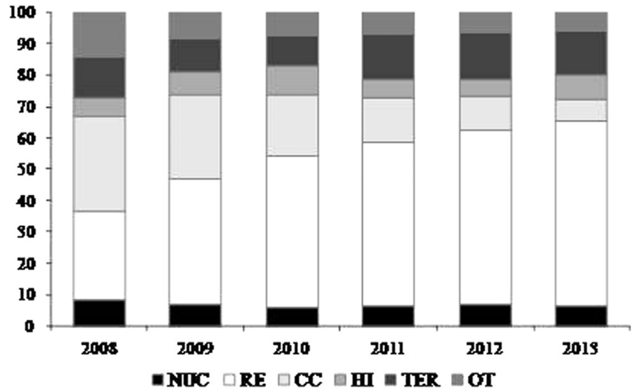

Fig. 1. Daily average share by technologies in the Spanish day-ahead market Technologies are: nuclear (NUC), renewable (RE), combined cycle (CC), hydraulic (HI), thermal (TER) and others (OT).

renewables in the day-ahead market was 28% of the total production in 2008 per day, on average, whereas five years later, in 2013, it had reached 58% of total electricity produced per day, on average, followed distantly by the remaining generating technologies (Fig. 1). This substantial change in the Spanish generation mix from conventional generation sources to renewables in a few years' time will likely be expected to have an impact on the price formation process.

The stylized facts of electricity have been widely pointed out in the literature [1–6]. Due to its well-known intrinsic features, such as its non-storable nature, electricity prices traditionally exhibit high volatility. As well, extreme observations, outliers (atypical values) or jumps normally occur more frequently than with other commodities or financial assets.

The advancement in renewable generation provides social and environmental benefits related to key areas such as rural development, employment or health, as highlighted by Burgos-Payán et al.[21], and that are not always easy to quantify. In addition, it may also involve changes in the electricity market, with economic impacts.

Several concerns arise when assessing the impact of renewables on the behaviour of electricity prices. These concerns are related to the fact that most of the renewable production is intermittent and somewhat unmanaged. Thus, for instance, wind production depends heavily on the wind speed and direction. In this sense, many voices claim that this intermittent nature of output from renewables will be transferred to electricity prices, with the result of an increase in uncertainty and, hence, in greater price volatility and price risk. The intermittency of renewable generation, when compared to conventional power sources such as nuclear or fossil fuels, which are assumed to be much more secure and reliable, together with the fact that electricity cannot be easily stored, are the main arguments usually given to explain why prices should become even less predictable, and hence more volatile, as long as generation from renewable sources increases. In addition, it is this intermittency that may lead to increases in both the number and magnitude of the so-called price jumps. It should be noted, however, that fuel cost volatility may also be transferred to electricity prices. Therefore, the displacement of conventional power sources by renewable generation may contribute to reduce price volatility,[1] instead of increasing it, which is just the opposite effect of the one which is anticipated by those who alert against the use of renewables due to the above-mentioned arguments.

A quite generalized idea related to the impact of the inclusion of renewables as a new generation source in the electricity market is that it will presumably cause a decrease in marginal prices. The reason behind this is that renewable producers can be considered as *price takers* since they offer very low (close to zero or even zero) prices. Thus, an increase in the amount of these *low* price offers is expected to shift the supply curve to the right with the result of lower marginal prices. Lower prices for electricity would undoubtedly have positive effects for both consumers and firms, given that the latter use electricity as an input in their manufacturing process. Therefore, a decrease in electricity prices may also contribute to increasing overall productivity.

The goal of the present work is to verify whether the above-mentioned assumptions have been verified in practice, once the penetration of renewables has been significant enough. Thus, the questions to be answered include:

(i) whether marginal prices may have decreased as a consequence of the entrance of renewables into the system,
(ii) whether marginal prices have become more volatile, and finally,
(iii) whether marginal price jumps occur more frequently than before.

The relationship between renewables and electricity prices has captured the attention of many authors in the literature on energy markets: [7] present an overview of research results on the price effect of renewable production. A common pattern can be observed: in all markets using a merit order dispatch system, generators with lower marginal costs, such as renewable producers, contribute to reducing marginal prices;[8] compare two days with different levels of renewable production but with a similar demand in 2006 in the Spanish case to find that the cost of supporting the development of renewables, initially considered to be very expensive, may have been compensated for by the subsequent decrease in electricity prices; [9] obtain the same conclusions for the German market, in 2006; [10] investigate the economic impact of a large amount of renewables in the Nordic Countries. By employing simulations, they conclude that high penetrations of wind power may push the Nordpool spot market prices down; [11] state that increments in photovoltaic electricity generation lead to lower marginal prices in the Australian electricity market; [12] after studying the effect of weather conditions in the Dutch electricity market (period 2006–2011), find that an increase in wind speed negatively affects electricity prices; Finally, [13] carry out an ex-post analysis of the effect of renewables and cogeneration in the Spanish electricity market. By using a database of hourly data from 2005 through 2009, their results lead them to conclude that a marginal increase in renewable production of 1 GW h could be associated with a reduction of almost 2€/MW h in marginal electricity prices.

The Spanish case is chosen as a paradigmatic example to embrace the analysis due to the massive introduction of renewables sources into the Spanish generation mix during recent years. To learn about the particular supply-demand situation in the Spanish electricity day-ahead market, Fig. 2 shows the 24-load curves of four typical days of 2013, one Wednesday a season. Each day has been selected to be Wednesday in order to make them comparable each other. Together with the offered demand, it is represented the offered supply too. Intra-daily seasonality appears to be significant. Thus, the offered supply and the offered demand are generally lower for off-peak hours[2] and, particularly from hour

[1] We wish to thank an anonymous reviewer for pointing out this impact on price volatility that may even compensate the previously exposed.

[2] Peak hours refers to hours from 8:00 h to 20:00 h on business days, while off-peak hours refers to hours from 00:00 h to 8:00 h and from 20:00 h to 24:00 h on working days and the whole day on weekends and holidays.

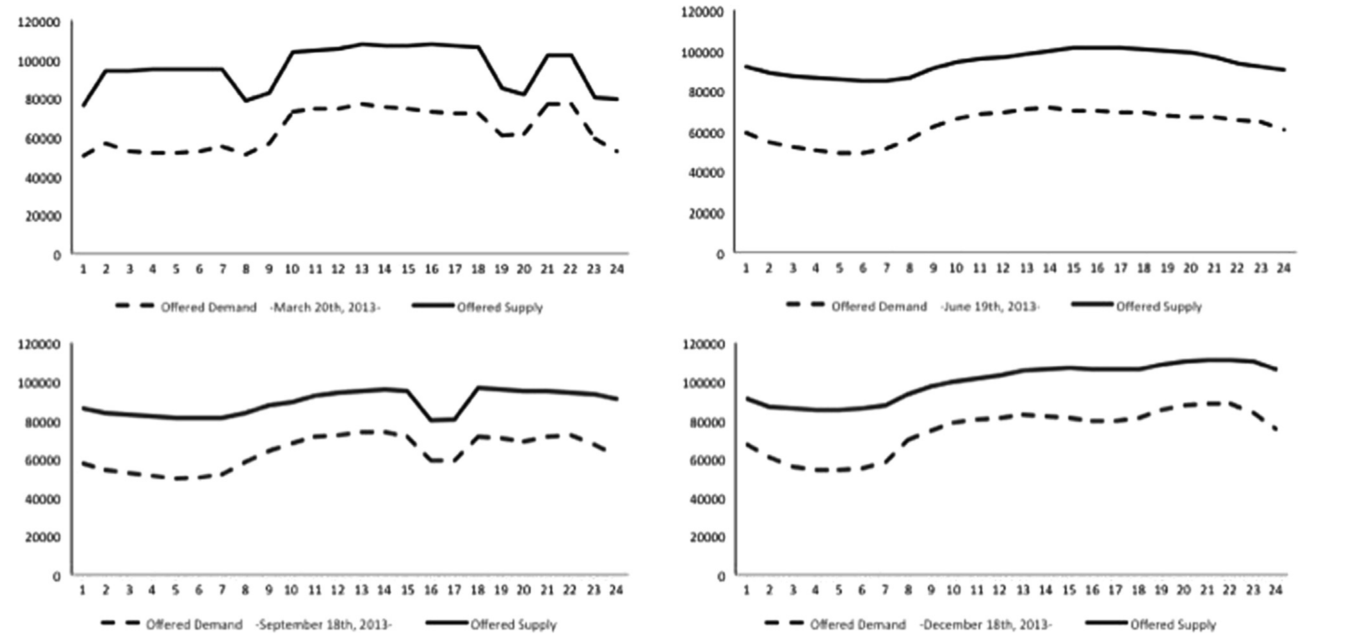

Fig. 2. 24-h load curves of four typical days in 2013 (MW h).

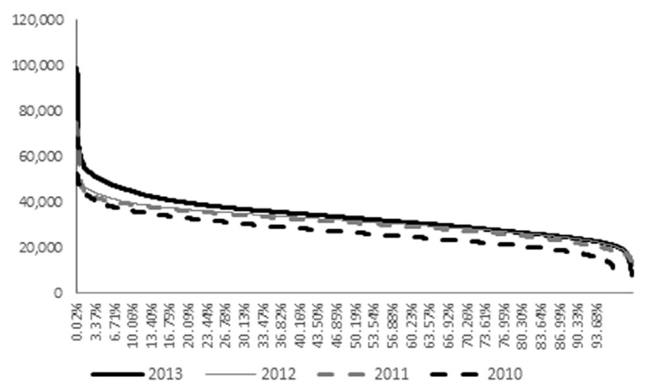

Fig. 3. 8760-load duration curve for the difference between offered supply and offered demand (MW h) for 2010–2013.

1 to 8. Similar figures for other two years of the sample period, namely, 2012 and 2010, are presented in Appendix (Figs. A.1. and A.2). As can be observed, in all cases, the offered demand is lower than the offered supply, indicating that there is a permanent situation of excess supply in the market.

In addition, the 8760- h load duration curves for the difference between the offered supply and the offered in the last four years of the sample, 2010–2013, is shown in Fig. 3. As can be seen, it is evidenced the excess of supply over demand for every considered year, though such an excess is progressively higher from 2010 to 2013. It is also remarkable the peak observed in 2013. The insight obtained from this graphical analysis is consistent with the fact that the installed capacity is higher in 2013, mainly due to the continuously increasing penetration of renewables into the system.

The results of the present study are of interest for both portfolio managers and practitioners, who, being aware of the need to hedge the price variation risk, aim to properly know the true characteristics of price behaviour. In fact, it is the intermittency of renewable generation that is claimed to be responsible for greater price volatility as well as contributing to an increase in the frequency of price jumps. The higher the price volatility, the greater the need to hedge power portfolios in order to minimize the negative effect of adverse price fluctuations.

We extend the previous literature by analyzing the effect of electricity generated by renewable sources on marginal prices, once a sufficiently long enough sample period is available. This period consists of approximately six years of data, since 2008, and may be compared to the earlier years of the whole sample. Besides, the undertaken analysis is more complete than the previously mentioned works, since it does not only cover the effect of renewables on the level of prices but also on price volatility and on the frequency of jumps, taking a two-prong approach. In a first step, a preliminary descriptive analysis is performed, that is certainly helpful to gain overall insights into the research questions addressed by this study and to identify which issues require a more in-depth analysis, which will be carried out in a second step, using econometrical tools.

The rest of the paper is structured as follows. Section 2 describes the data used. Section 3 presents an overview of the changes in the technologies that set marginal prices for the period 2001–2013, the evolution of the day-ahead market marginal price statistics, as well as of variations in the power generation mix within the period of study. Section 4 is devoted to an empirical analysis of the impact of the renewables share on the marginal price, on the number of times each technology sets the marginal price and on the marginal price volatility and jumps. Section 5 summarizes the obtained results and concludes.

2. Data

The dataset used consists of Spanish day-ahead market marginal prices and the generation sources or technologies setting marginal prices with an hourly frequency, from 2001 to 2013. Furthermore, we have employed the amount of electricity produced by technology from 2008 to 2013.This dataset is available at the OMIE webpage,[3] where renewables are referred to as *special regime*. The special regime includes mainly wind[4] but also solar, co-generation, biomass and waste treatment. From now on, we

[3] www.omie.es (last accessed April 2014).

[4] In 2013, the 49% of the *special regime group* comes from wind, whereas the percentages for co-generation, solar, and the remainder included technologies

will refer to this group as renewable generation sources, RE, in which hydroelectric plants are not included, and to refer to the remaining technologies, the following nomenclature will be used: TER (thermal: coal and oil-gas), NUC (nuclear), HI (hydroelectric), BG (pumping hydropower) and CC (combined cycle).

Finally, the offered demand and supply hourly volumes submitted to the day-ahead market in of the period covering from 2010 to 2013 have been used to build the corresponding 24-h load curves and the 8760-h load duration curve that are referred to in Section 1.

3. Preliminary analysis

3.1. Technology setting the marginal price

In the Spanish day-ahead market, prices and quantities of electricity are determined through a uniform price auction for each delivery hour of the following day. The price for each hour is the one paid by market participants whose purchase bids have been accepted after the bid matching process. This price, called the *marginal price*, equals the price of the last sale bid whose acceptance has been required in order to meet the matched demand.[5] Then, it is very relevant to identify the technologies and trading strategies of those plants that set the marginal price, and see whether there have been any changes in the technologies setting the marginal price throughout the considered period, and, specifically, during the period of the sample in which the participation of renewables became significant.

These submitted offers will typically be dependent upon the variable generating costs of the referred technologies but also on the expected offered prices and quantities submitted by the rest of the market participants. Sometimes, more than one offer unit sets the marginal price for a specified hour because they bid at the same price. Indeed, each technology has 24 occasions a day to set the marginal price.

Sale bids from renewable generators are frequently very low. For that reason, *a priori* they should not be expected to be among the technologies normally setting the marginal price. However, their increasing presence may have altered the supply curve and affect the probability of other generation technologies to determine marginal prices.

Table A.1 in Appendix shows the average percentage of times a day that each technology sets the marginal price from 2001 to 2013. According to it, four different periods can be distinguished:

i) 2001–2003, in which the main technologies determining the marginal price were HI and TER (approximately 36% on average for base-load prices).
ii) 2004–2009, a period in which the most remarkable thing is the huge increase in CC setting the marginal price.
iii) 2010–2013, in which the number of times that CC sets the marginal price decreases in favour of other technologies, mainly TER and HI. During this period, on average, RE sets marginal prices 9.5% (7.4%, 10.5%) of the time for base-load (peak, off-peak) prices.

When distinguishing between peak and off-peak hours, on the one hand, the leading role of HI for peak hours can be observed. In fact, HI occupies the first place, on average, for all the studied periods except for the period 2005–2009 when it is replaced by CC. The number of times HI sets the marginal price is especially high in 2003, 2010 and 2013. These were very wet years, which allowed reservoirs to reach high water levels (above 60%).[6] On the other hand, it is TER that holds the leader position during 2001–2005 and 2011–2012, for off-peak hours. For the period 2006–2010, CC exceeds TER in terms of the number of times it sets the marginal price, whereas in 2010 and 2013 HI becomes the leader.

It is also interesting to see the difference in setting marginal prices by pumping hydropower (BG) between peak and off-peak hours. The number of times the BG technology sets the marginal price reaches 30% in peak hours, whereas this value is much lower for off-peak hours, around 7%.

3.2. Descriptive statistics of the day-ahead market marginal prices.

Fig. 4 shows the evolution of the Spanish day-ahead market marginal price for the period 2001–2013. Table A.2 in Appendix shows the main descriptive statistics of marginal price by years, distinguishing between peak (Panel B) and off-peak (Panel C) prices.

The lowest base-loadprices on average, around 30 Eur/MW h (Table A.2, Panel A), are those from the early years in the sample, namely 2001, 2003 and 2004. Then, it is in the period 2005–2008 when average marginal prices reach their highest level, around 50 Eur/MW h, and they are particularly high in 2008 (64Eur/MW h). This period coincides with years of drought and low water reservoir levels, as well as with the entrance of combined cycle plants. In the following two years, 2009–2010, prices drop up to 37 Eur/MW h on average. During this period, the drought ends and there is a notable penetration of renewables into the system. However, for 2011–2012, despite the increasing contribution of renewables to electricity production, prices rise again up to levels near 50 Eur/MW h, followed by a slight reduction in prices during 2013. Mean-peak (Table A.2, Panel B) and off-peak (Table A.2, Panel C) prices are shown to follow the same pattern as base-load prices, though, as expected, peak prices are always higher than off-peak prices.

Looking at the standard deviation of daily marginal prices obtained as the daily average of the 24 hourly marginal prices, there is no clear evidence that price volatility has increased as a consequence of renewables for the Spanish case. Only in the last year of the studied sample, 2013, is standard deviation notably higher than in previous years. As can be observed, skewness takes negative values for the later years in the sample, meaning that prices that are below the mean are more frequent than prices exceeding it. This result, *a priori*, would be consistent with the idea that more renewable production can lead to lower prices. Finally, kurtosis indicates the degree of peakedness of a distribution relative to the normal. According to our results, it seems that the distribution of marginal prices are generally becoming narrower for the last years of the sample.

As mentioned in the introduction section, prices would be expected to become more and more extreme as a consequence of the presence of renewables. A great number of extreme values in the price distribution may be a problem when trying to predict prices. In the literature, before estimating a model, the values that are considered to be too far from the central points of the distribution, normally called outliers, are usually replaced by other *more normal* values or even ignored. To get some preliminary evidence about the evolution of extreme values throughout the studied sample, Table A.2 also includes the percentage of prices

(*footnote continued*)
(biomass, waste treatment and mini hydraulic are 29%, 11%, 11% and 11%, respectively (⟨www.ree.es⟩, last accessed May 2015).

[5] Within the context of electricity, the so-called spot markets are actually day-ahead markets and the marginal prices resulting from the day-ahead market auction are frequently referred to as spot prices.

[6] ⟨www.ree.es⟩.

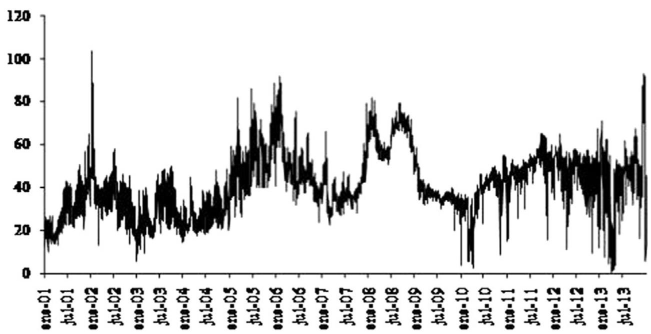

Fig. 4. Marginal prices in the Spanish day-ahead market.

that could be considered as outliers. In this work, outliers are identified following the procedure described in [14], which consists of defining an outlier as any value which is outside of the interquartile range, i.e. Q3–Q1 (where Q1 and Q3 are, respectively, the first and the third quartiles).

From Table A.2, it can be observed that for the first three years of the sample, 2001–2003, 3.3%, 4.7% and 6.6% of base-load marginal prices can be considered as outliers, according to the described procedure. During the following years there are quite few outliers, except for the approximately 5% of outliers found during 2004–2005 in peak prices. From 2010 onwards, the number of outliers generally increases, reaching similar levels to the first period. Finally, in 2013, 15% of the observations can be considered as outliers. Furthermore, we note the huge differences found when peak and off-peak hours are analyzed separately. Thus, in contrast to what happened in the first years of the sample (years without renewables), from 2010 onwards, the number of outliers in the time series of off-peak prices becomes much larger than in peak hours.

3.3. Electricity generation by technology type

The weight of RE has significantly grown, increasing from 29% in 2008 to 59% in 2013, on daily average. Since 2011, on some days it has even amounted to 80% of the total production. 78% on average of the energy matched in the Spanish day-ahead market for the period covering 2008–2013 comes mainly from three generating technologies: renewables (RE), combined cycle (CC) and thermal plants (TER). Hydroelectric (HI) occupies the fourth place, with 7% in 2013.

Table A.3 shows the share of electricity production by generation source, by year, from 2008 through 2013, distinguishing between peak and off-peak prices. It is interesting to observe the continuous growth of RE throughout the sample, which contrasts with the progressive reduction of CC, declining from 30% in 2008 to 7% in 2013. Regarding HI share, it is really quite variable over the years because it strongly depends on annual rainfall and reservoir water levels. Thus, during wet (dry) years, the hydraulic generation actively (hardly) participates in the total production of electricity. Finally, TER share decreases for 2009–2010, though to a lesser degree than CC, to recover a predominant position since 2011. The reason behind this may be found in a new regulation that entered into force in February 2011 (the Royal Decree 134/2010), whose aim was to achieve a minimum level of electricity produced by using domestic coal.

In addition, we must take into account that the studied period includes the global financial and economic crisis. In 2009, Spanish GDP growth became negative, −3.8%, and economic activity was considerably reduced, causing a notable decrease in energy demands, -4.7%.[7] The crisis went on during the later years of the sample. Under this context, it should be highlighted that the proportion of renewables keeps growing, during both peak and off-peak hours.

NUC share has reduced slightly overtime, whereas BG share, being more residual (2.5% on average), was increasing during 2008-2012.

4. Empirical results

The aim of this section is to investigate by using econometric tools, the role that renewable electricity production may have played in the Spanish day-ahead market, particularly, whether:

(i) RE share may have effectively altered the number of times each technology sets the marginal price;
(ii) Marginal prices may have on average decreased as a consequence of the penetration of renewable generation sources into the Spanish electricity system;
(iii) Price volatility may have increased and been explained by RE share volatility; and
(iv) RE share may have made price jumps more frequent.

4.1. Renewable share and technology setting marginal price

To study whether the RE share may explain the frequency with which each technology sets marginal price, the following linear regression model is used:

$$m_{e,t} = \alpha_e + \beta_e * \mathrm{RE}_t \tag{1}$$

where $m_{e,t}$ is the percentage of times the technology e sets the marginal price in the day-ahead market on day t and RE_t is the percentage of renewables in the produced electricity in the day-ahead market on day t (RE share).

Estimation results are shown in Table 1. As can be seen, there is a significantly positive relationship between RE share and the percentage of times that TER, HI and BG set the marginal price, whereas such a relationship is statistically negative between RE share and the percentage of times that CC does it. These results are confirmed for base-load, peak and off-peak hours, with the only exception being that for peak hours there is no statistical relationship between RE share and the percentage of times that HI sets marginal price. In this way it confirms the idea of RE affecting the probability of other technologies setting the marginal price. Particularly, it can be stated that CC, as technology setting the marginal price, may have been displaced, partially at least, by the irruption of renewables into the system in the Spanish case.

4.2. Renewable share and marginal price

As previously indicated, a greater amount of renewable production is expected to have an impact on the day-ahead price due to the auction mechanism itself. Thus, as renewables generators offer lower prices than most of the other agents in the market, this causes a shift to the right in the supply curve. To examine this issue, the following linear regression model is estimated with RE share as the independent variable:

$$P_t = \alpha + \beta * \mathrm{RE}_t \tag{2}$$

where P_t refers to the marginal price in the day-ahead market on day t and RE_t is the RE share on day t.

As can be seen in Table 2, the beta coefficient is negative, meaning that the marginal price will likely decrease with an increase of RE share, and vice versa, confirming that RE share has the expected effect on the marginal price. In this way, the

[7] ⟨www.ree.es⟩.

Table 1
Estimates of Model (1).
Ordinary least squares estimates of the univariate model (1). Renewable (RE) share is the independent variable and the dependent variable is the number of times each technology sets marginal price. The considered technologies are: combined cycle (CC), thermal (TER), hydraulic (HI) and pumping hydropower (BG). The Newey-West correction is used to control for heteroscedasticity and serial correlation.

	CC		TER		HI		BG	
	Value	t-Statistic	Value	t-Statistic	Value	t-Statistic	Value	t-Statistic
Base-load hours (00:00–24:00)								
α	63.7430**	31.96324	14.8768**	11.41163	16.1352**	9.307617	10.22145**	9.579982
β	−0.73435**	−18.97935	0.214637**	7.461359	0.38346**	10.22468	0.112069**	5.179323
Adjusted R^2	0.273002		0.035664		0.101389		0.021506	
Peak hours (08:00−20:00, business day)								
α	50.31431**	17.45870	7.376469**	3.927244	35.07231**	13.02311	18.80578**	9.737366
β	−0.553015**	−10.19001	0.258551**	6.055620	0.095845	1.764.239	0.085766*	2.232375
Adjusted R^2	0.120268		0.037509		0.003509			
Off-peak hours (00:00–08:00 and 20:00–24:00, business day, 00:00–24:00 holidays)								
α	73.94679**	33.15469	19.26772**	12.73165	4.286219*	2.406686	3.994430**	4.462314
β	−0.878278	−20.17791	0.185395**	5.750539	0.562738**	13.91629	0.147374**	7.647749
Adjusted R^2	0.298063		0.020864		0.168985			

Statistical significance at the 1% (5%) level is denoted by ** (*).

Table 2
Estimates of Model (2).
Ordinary least squares estimates of the univariatemodel (2).The dependent variable is the marginal price, while renewable (RE) production share is included as the explanatory variable. The model is re-estimated by substituting the RE share with the following alternative technologies: combined cycle(CC), thermal (TER), hydraulic(HI), pumping hydropower (BG) and nuclear (NUC).The Newey-West correction is used to control for heteroscedasticity and serial correlation.

	RE		CC		TER		HI		BG		NUC	
	Value	t-Statistic	Value	t-Statistic	Value	t-Statistic	Value	t-Statistic	Value	t-Statistic	Value	t-Statistic
Base-load hours (00:00–24:00)												
α	70.29**	34.31	38.15**	29.05	31.02**	22.44	57.07**	48.69	47.69**	32.08	51.89**	24.22
β	−0.50**	−13.18	0.47**	7.00	1.21**	14.40	−1.48**	−10.61	−0.52	−1.11	−0.77*	−2.33
Adjusted R^2	0.27		0.14		0.36		0.20		0.00		0.02	
Peak hours (08:00–20:00, business day)												
α	75.61**	27.12	43.49**	24.20	38.21**	20.80	61.50**	34.92	53.01**	26.86	56.75**	18.52
β	−0.51**	−9.54	0.42**	4.84	1.07**	10.01	−1.36**	−5.53	−0.32	−0.69	−0.86	−1.46
Adjusted R^2	0.25		0.11		0.27		0.11		0.00		0.02	
Off-peak hours (00:00–08:00 and 20:00–24:00, business day, 00:00–24:00 holidays)												
α	65.45**	33.69	36.39**	28.48	28.04**	20.87	53.30**	50.75	45.43**	35.58	48.33**	22.27
β	−0.46**	−12.84	0.42**	6.36	1.19**	14.45	−1.39**	−11.64	−1.17*	−2.21	−0.61*	−2.03
Adjusted R^2	0.25		0.11		0.37		0.22		0.00		0.01	

Statistical significance at the 1% (5%) level is denoted by ** (*).

entry of renewables into the system would have contributed to reducing the price resulting from the day-ahead market auction.

However, as seen in Table A.2 and already commented on in the previous section, despite the fact that RE share has been considerably higher for the later years in the sample period, marginal prices on average have not decreased. To shed some light on this issue, the regression model (2) has been newly estimated by substituting RE with each of the other generation sources. According to the results shown in Table 2, similarly to RE share, HI presents a statistically negative relationship with (base-load, peak and off-peak) marginal prices. It is also found a significantly negative relationship between NUC and (base-load and off-peak) prices and between BG and (off-peak) prices.

Regarding the other types of generation sources, a significantly positive relationship is found between TER and CC shares with regards to the marginal price, which is an expected result given that they are technologies with higher generation variable costs.

Therefore, to answer the question set out at the beginning of this section, marginal prices get reduced with renewables, which is in line with previous literature ([8,13], among others).

4.3. Renewables share and price volatility

As mentioned in the Introduction, electricity prices traditionally exhibit high volatility. Furthermore, the so-called price jumps are assumed to be relatively frequent. One of the most important concerns about the integration of renewables into the system is that the intermittent nature of these technologies may increase price volatility as well as the number of price jumps, which would end up creating more difficulties when modelling electricity prices, due to greater uncertainty. Then, what needs to be determined is:

(i) whether RE generation may be behind price volatility, and
(ii) whether RE share volatility may contribute to the presence of price jumps.

In order to find this out, the model proposed by Benth et al. [15], which was later applied to the electricity market by Cartea and Figueroa [16], is chosen. This model aims to describe the main features of electricity prices and it is especially interesting for the purposes of this study, as it allows price volatility and jumps to be captured.

The model adapted by Cartea and Figueroa [16] is a stochastic process with mean reversion that includes a discrete jump process (a diffusion model). Under this model, jumps are defined as large price movements at a particular point that break the continuous process followed by the price, and price volatility is calculated day-to-day with a moving window of 30 days. Once estimated, the next step will be to study whether the obtained estimates may have been altered by changes in the electricity production from renewable sources.

4.3.1. Model definition

We have $(\Omega,\ P,\ F,\ \{F_t\}_{t\ c\ [0,\ T]})$ a filtrated and completed probability space with finite time horizon $T<\infty$. The spot price on time t, $0<=t<=T$, is defined as:

$$P_t = \exp(f(t)+Y(t)) \tag{3}$$

where $f(t)$ is a deterministic function that captures seasonal tendency and $Y(t)$ is a stochastic process whose dynamics are:

$$dY_t = -\alpha Y_t \mathrm{d}t + \sigma(t) dZ_t + \ln J dq_t \tag{4}$$

Y_t is a diffusion process with jumps and mean reversion of the spot price P_t; $\sigma(t)$ is the volatility that depends on time; J is the size of the random jump; dZ_t is the increment of standard brownian and dq_t is a Poisson process where l is the intensity or frequency of the process (dq_t is equal to 1 with probability ld_t or it is equal to 0 with probability $(1-ld_t)$).

J is Lognormal:

$$j->N(\mu_t,\sigma_t^2)$$

$$E(J)=1$$

Their properties are

$$J=\exp(\phi), \phi->N(-\sigma_t^2/2, \sigma_t^2)$$

$$E[\ln J] = -\sigma_t^2/2$$

$$\mathrm{Var}[\ln J] = \sigma_t^2 \tag{5}$$

The steps to estimate the parameters of the model are as follows:

1. Transformation of the price series in log returns. Previously, once the outliers are identified using the method described in Section 3, they are replaced by the average of their neighbouring values.[8]
2. Estimation of the long-term trend T_t. The function proposed by [17] is used, a sinusoidal function supplemented by an exponentially weighted moving average (EWMA), being $\lambda=0.975$ (value recommended by [17]). Parameters are estimated by nonlinear least-squares, using the Gauss–Newton option on PROC NLIN of SAS.The function is
$$T_t = a_1 + \sin\{2\pi((t/365)+a_2)\} + a_3 + a_4\,\mathrm{EWMA}_t^\lambda$$
$$\mathrm{EWMA}_t^\lambda = (1-\lambda)P_t + \mathrm{EWMA}_{t-1}^\lambda \tag{6}$$
3. Once the long-term trend defined in the previous step is subtracted, a second seasonal component, S_t, is calculated, which is equal to weekly average.
4. Following [16], the mean reversion is estimated through the following equation:
$$Y_{t+1} - Y_t = \alpha Y_t + \varepsilon_t \tag{7}$$
where Y_t is the price in logarithms without seasonal components and α is the mean reversion parameter, which is estimated by ordinary least squares.
5. To calculate the price volatility in the model, as it is considered not to remain constant over time, the standard deviation is calculated for a moving window of 30 days, namely, price volatility is calculated day-to-day with a moving window of 30 days.
6. The technique used to identify jumps in our sample is the one used in [16,18]. It consists of an iterative algorithm that filters the returns whose absolute value exceeds the standard deviation multiplied by three. The values marked as jumps are replaced by the average of its non-marked neighbours and the procedure goes on until all values in the sample are non-marked values.

Table 3 (Panel A) shows the estimation results of the diffusion model with jumps and mean reversion (4) for the period 2008–2013, when a non-negligible amount of electricity generation comes from renewable sources, distinguishing between peak and off-peak hours. Firstly, some relevant differences between peak and off-peak hours appear. Thus, the price volatility is higher for off-peak than for peak hours, 0.15 *versus* 0.9. As well, the frequency of jumps is also notably higher for off-peak hours, whereas the mean reversion is not much lower as indicated by the value of the α coefficient. Secondly, in order to study jumps in detail, the number of jumps is also shown (Panel B), distinguishing between the negative and the positive ones, not only for peak but also for off-peak hours. As can be observed, negative jumps are much more frequent than positive for base-load (62 *versus* 33), peak (38 *versus* 16) and off-peak (75 *versus* 40) hours.

Fig. A.3 shows the evolution of jumps throughout the years in the sample. It should be noted the large number of jumps recorded from January to May, in 2010 and in 2013 which contributed to increasing volatility during these two periods (as can be seen in Fig. 5), and which was even more notable for off-peak hours.

In order to measure the relationship between RE share volatility and price volatility, the Pearson test is used. The two detected high volatility periods, i.e., from January to May, 2010, and from January to May, 2013, have been analyzed separately for peak and off-peak hours. Results are shown in Table 4. As can be observed, there is a positive linear relationship between RE share volatility and price volatility for the whole sample, which becomes stronger when excluding the two high-volatility periods mentioned above, when the correlation coefficient reaches 63%, in peak and off-peak hours. Compared to the rest of technologies, this is the highest Pearson test value obtained. Therefore, increases in RE volatility are accompanied by increases in price volatility. This result is consistent with the results of [19] for the English market.

Nevertheless, it is relevant to mention that significant positive relationships have also been found, above all when excluding the two detected high-volatility periods, between the price volatility and the volatility of the shares of technologies other than RE, such as TER HI, NUC and BG. Furthermore, another very interesting point is the significantly negative relationship obtained between the CC share volatility and the (base-load and off-peak) price volatility.

Focusing on the two periods with the greatest price volatility, namely, from January to May 2010, and from January to May 2013, the correlation is notably higher for HI, NUC and BG for base-load and off-peak hours, and even the sign of the correlation between RE share and price volatility becomes negative. In fact, as is shown

[8] It should be emphasized that these values are normally excluded and not employed in estimation because they are considered to cause serious distortion. Next, it is crucial to know the number of potential outliers that can be expected within a particular series, and for those series with many outliers, alternative methods are needed, since the removal of them may cause a loss of information which would translate into less efficient estimates.

Table 3
Estimation results of the diffusion model with jumps and mean reversion (4).
Panel A shows the diffusion model estimates, distinguishing between peak and off-peak hours*: a*1, *a*2, *a*3 *and a*4 are the parameters used to adjust the long-term seasonal component T_t, (7)*;* [σt] *is the mean* 30 days volatility of the price*;* α indicates the reversion to the mean, and σj, *l* are the jump parameters, namely standard deviation and frequency of the jumps, respectively. Panel B, presents detailed information about the number of outliers, total, positive and negative jumps detected in the sample.

Panel A parameters	*a*1	*a*2	*a*3	*a*4	[σt]	α	σj	*l*
Base-load hours (00:00–24:00)	−0.0412	110.2	−2.0171	2.6769	0.12	0.23064	0.82	15.833
Peak hours (08:00–20:00, business day)	−0.00429	110.2	−2.0519	2.6928	0.09	0.21406	0,43	9
Off-peak hours (00:00–08:00 and 20:00–24:00, business day, 00:00–24:00 holidays)	−0.0450	110.2	−19.715	26.550	0.15	0.18140	0.10305	19,167
Panel B outliers and jumps	Total	2008	2009	2010	2011	2012	2013	
Base-load hours (00:00–24:00)								
Outliers	145	0	3	32	12	30	68	
Jumps	95	0	3	16	8	21	47	
Positive jumps	33	0	2	3	4	6	18	
Negative jumps	62	0	1	13	4	15	29	
Iterations	6							
Peak hours (08:00–20:00, business day)								
Outliers	79	0	3	14	3	16	43	
Jumps	54	11	1	15	2	9	26	
Positive jumps	16	0	1	5	1	3	6	
Negative jumps	38	11	0	10	1	6	20	
Iterations	5							
Off-peak hours (00:00–08:00 and 20:00–24:00, business day, 00:00–24:00 holidays)								
Outliers	128	1	2	26	15	23	61	
Jumps	115	0	7	32	8	21	47	
Positive jumps	40	0	2	15	1	5	17	
Negative jumps	75	0	5	17	7	16	30	
Iterations	11							

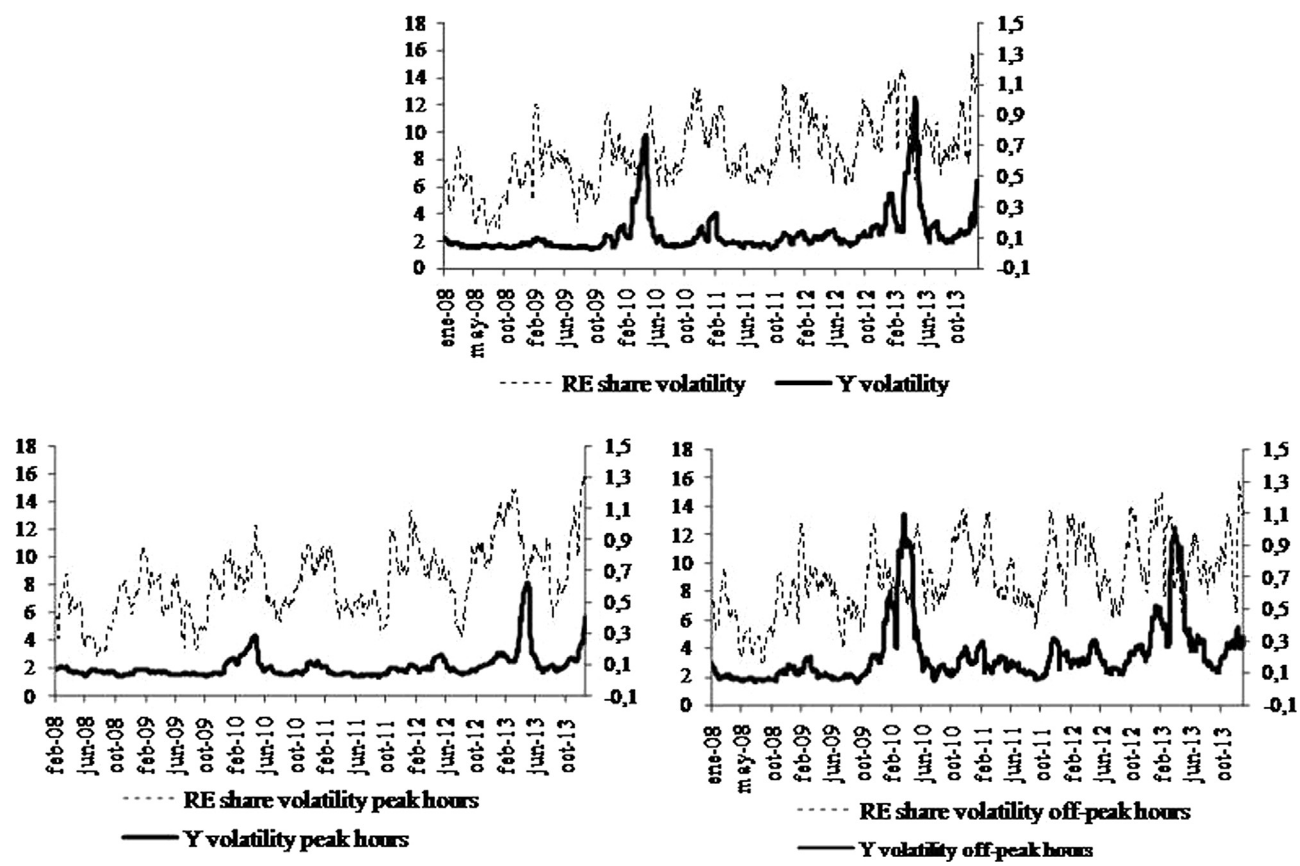

Fig. 5. RE share volatility and base-load marginal price without seasonal component (*Y*) volatility.

in Fig. 6, volatility peaks in HI, NUC and BG generation match marginal price volatility peaks better than RE.

Therefore, the volatility of the electricity produced by the different generation technologies involved in the present study has been transferred to prices, with the only exception of CC, which presents no relationship at all with peak prices volatility and a significantly negative one with (base-load and off-peak) prices volatility.

Table 4
Marginal price volatility and production share volatility by technologies.
Pearson test between marginal price (without seasonal component) volatility and the production share volatility for different generation technologies, distinguishing between peak and off-peak prices. Included technologies are: hydraulic (HI), pumping hydropower (BG), nuclear (NUC), combined cycle (CC) and thermal (TER).

	RE	CC	TER	HI	NUC	BG
Base-load hours (00:00–24:00)						
Total	0.27978**	−0.19049**	0.15136**	0.73057**	0.54517**	0.50646**
Excluded Jan 2010–May 2010 and Jan 2013–May 2013	0.63852**	−0.2125**	0.60925**	0.3417**	0.2564**	0.50315**
Jan 2010–May 2010 and Jan 2013–May 2013	−0.26351**	−0.15735**	−0.16887**	0.68028**	0.67888**	0.72605**
Peak hours (08:00–20:00, business day)						
Total	0.55748**	0.02774	0.30428**	0.67605**	0.48723**	0.45195**
Excluded Jan 2010–May 2010 and Jan 2013–May 2013	0.63255**	−0.03463	0.52936**	0.37192**	0.21579**	0.36904**
Jan 2010–May 2010 and Jan 2013–May 2013	0.01435	0.03957	−0.14151*	0.65415**	0.49694**	0.58671**
Off-peak hours (00:00–08:00 and 20:00–24:00, business day, 00:00–24:00 holidays)						
Total	0.26882**	−0.19898**	0.18314**	0.70779**	0.57265**	0.57316**
Excluded Jan 2010–May 2010 and Jan 2013–May 2013	0.62358**	−0.21330**	0.61021**	0.25600**	0.38560**	0.53368**
Jan 2010–May 2010 and Jan 2013–May 2013	−0.35802**	−0.16690**	−0.19043**	0.67545**	0.66119**	0.71528

Statistical significance at the 1% (5%) level is denoted by ** (*).

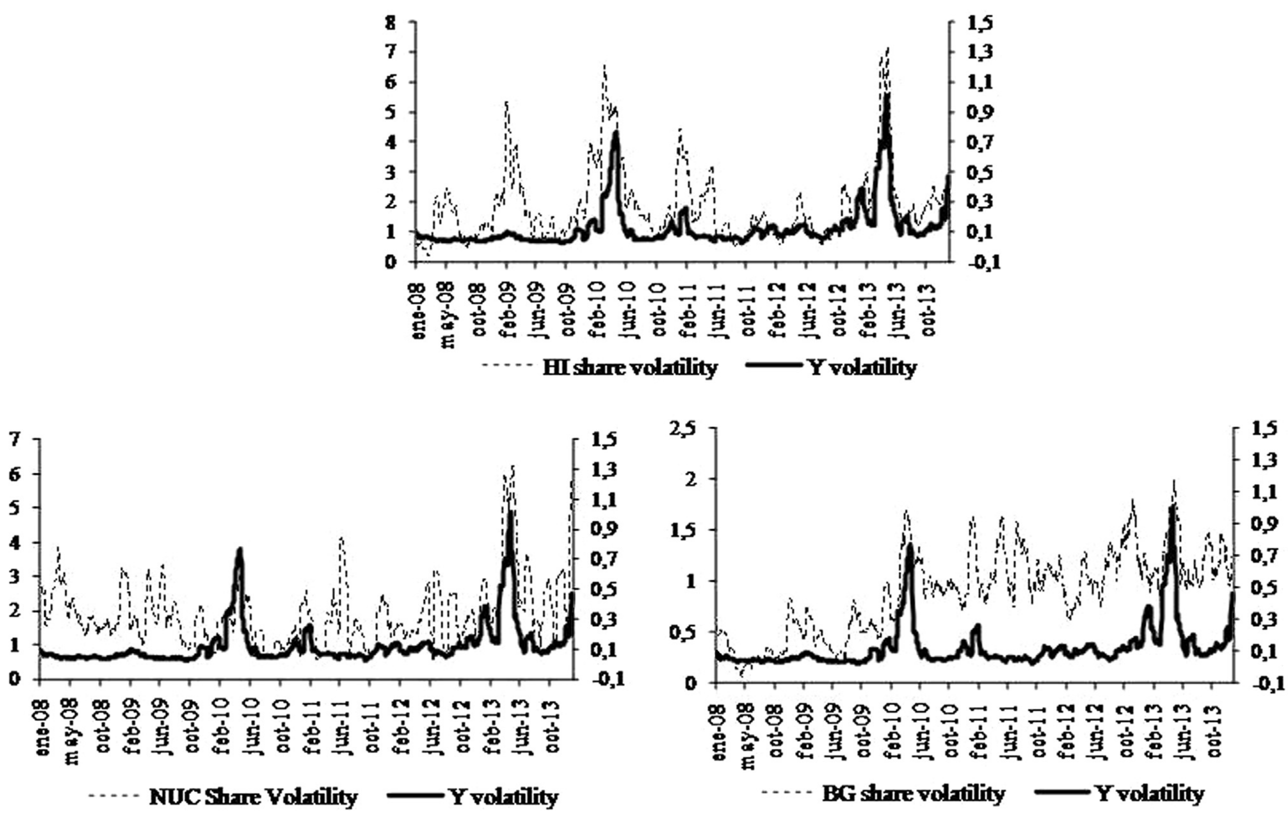

Fig. 6. Base-load Marginal price without seasonal component (Y) volatility, hydraulic share (HI) volatility and pumping hydropower share (BG) volatility.

Finally, in order to find out whether there has been a greater number of price jumps as a consequence of renewables, the jump process must be expressed as a function of the involved technology shares. A model for discrete choice, as that in [20], is adequate for this purpose because the event studied is a discrete event, meaning that it has only two possible outcomes: the jump event occurs or it does not. The model to be estimated is a logistic regression with the different generation technologies as explanatory variables:

$$\text{Logit}(\pi) = \text{Log}\,(\pi/(1-\pi) = \alpha + \beta' X \tag{8}$$

where π is the probability of a jump (in returns without seasonal component) and X is the matrix of time series in differences of six variables: RE share (d_RE), HI share(d_HI), BG share (d_BG), NUC share (d_NUC), CC share (d_CC) and TER share (d_TER).

With the aim of identifying the technology or technologies that may better explain the jump event, the automated procedure denominated stepwise (backward selection) is used. In the first step, the model does not include any variables. A chi-square test is carried out with each variable (seven variables, including intercept), and the variable that has the strongest relationship with the event enters into the model. In the second step, the exercise is repeated with the rest of variables. Once again, the best variable among those considered is chosen and the model is re-estimated with the two variables. If both variables were significant, they would both remain as candidates. However, if one or both were

Table 5
Logistic regression estimates. Model (8).
The dependent variable is the logit function of the probability of a negative jump event in the series of the day-ahead market returns,whereas explanatory variables are the generation share of different technologies, in differences: renewable share (d_RE), hydraulics(d_HI), pumping hydropower(d_HIB), nuclear(d_NUC), combined cycle (d_CC) and thermal (d_TER). The exercise is repeated with positive jumps as a new event and splitting the sample for peak and off-peak hours. The number of regressions are then 6: a, b and c for negative jumps and d, e and f for positive jumps. The coefficient c-statistics is a measure of association, and the LH test is the Hosmer and Lemeshov test of goodness-of-fit. This table only shows the group of variables that, following a stepwise procedure, turns out to be significant in each case.

Model	Negative jumps						Positive jumps					
	Base-load hours (00:00–24:00) (a)		Peak hours (08:00–20:00, business day) (b)		Off-peak hours (00:00–08:00 and 20:00–24:00, business day, 00:00–24:00 holidays) (c)		Base-load hours (00:00–24:00) (d)		Peak hours (08:00–20:00, business day) (e)		Off-peak hours (00:00–08:00 and 20:00–24:00, business day, 00:00–24:00 holidays) (f)	
Parameter	Value	Wald Chi-square	Value	Wald Chi-square	Value	Wald Chi-square	Value	Wald Chi-square	Value	Wald Chi-square	Value	Wald Chi-square
α	3.616	694.22**	-39.319	413.55**	-3.442	730.46**	-4.329	469.47**	−4.986	213.44**	-4.295	453.84**
d_RE							-0.07	96.19**	-0.109	14.88**		
d_HI												
d_BG					0.287	5.05*						
d_CC											0.078	5.27*
d_TER	-0.097	12.70**	-0.171	34.47**	-0.105	16.78**					0.110	8.03**
d_NUC											-0.147	4.47*
c-Statistic	0.591		0.702		0.642		0.632		0.708		0.716	
HL test	0.001	25.28	0.023	17.80	0.156	11.88	0.002	24.99	0.234	10.46	0.088	13.77
Jumps	62		38		75		33		16		40	
Obs.	2.191		1.523		2.191		2.191		1.523		2.191	

Statistical significance at the 1% (5%) level is denoted by ** (*).

not significant, then they would be ignored. The process continues as long as there are non-significant variables that may be considered as candidates for entering into the multivariate model.

The estimated results of the logistic regression are shown in Table 5.[9] The HL goodness-of-fit test shows if there is any evidence of a lack of fit in the selected model, and the c-statistic is a measure of association for the variables and the event. A c-statistic equals to 0.50 means that the model is not better than a completely random prediction. However, with a c-statistic equals to 1, then the fit is considered to be perfect.

Firstly, it should be pointed out that when using the time series of base-load prices (Table 5, models (a) and (d)), there is statistical evidence of lack of fit. Therefore, as estimation results are not valid, they are ignored. The reason can be found in the fact that the sample including the 24 price observations a day is made up of two very different levels of prices. So, price levels that would be considered as a positive (negative) jump under the distribution of off-peak (peak) prices may be considered as *normal* (meaning that it is not a jump) under the distribution of base-load prices. Then, when the prices for all the 24 h are put together, it turns out to be more difficult for the jumps in prices to be detected. Once the difference between peak and off-peak prices is detected, the picture is more informative.

Thus, starting with negative jumps in prices, it is observed that when TER share is higher than in the previous day, then the probability of a negative jump in the price decreases, for peak and off-peak hours, as indicated by the significantly negative parameter value (−0.17 peak hours, −0.10 off-peak hours). Additionally, the behaviour of BG share is also significant, having a positive effect on the probability of negative jumps, though the fact that this result only applies for off-peak hours is notable.

[9] Table 8 only shows in each case the group of variables that turned out to be significant at the end of the stepwise procedure.

Regarding positive jumps in prices, a statistically significant relationship is found between increases in RE share and the frequency of price jumps, though only for peak hours. However, the estimated parameter value is negative (−0.10), meaning that an increase in RE share would reduce the probability of positive jumps for peak prices. During off-peak hours, the technologies that would have an impact on the frequency of positive jumps would be: CC and TER, exhibiting positive values for the corresponding estimated parameters (+0.07 and +0.11 respectively), whereas for NUC it is displayed a significantly negative coefficient value (−0.14).

This is quite a striking result since, in contrast to the general belief that the introduction of renewable generation was going to give rise to extreme (positive) prices due to their intermittency and other supposed production planning and/or management problems, our results lead us to conclude just the opposite for the Spanish case. Indeed, it is the probability of a positive jump in peak prices (at the end, higher prices) that is reduced with increases in renewable generation. With regards to off-peak hours, there seems to be no statistical relationship between changes in renewables generation and jumps in prices.

5. Conclusion

The promotion of renewable energy sources in electricity systems has been a priority all over the world to deal with climate change. The advance of renewable technologies has environmental and social benefits, but it also involves economic impacts. The integration of clean energy sources is expected to cause relevant changes in electricity prices. In this work, we focus on the Spanish electricity market to shed some light on this matter.

Together with the evidence obtained regarding the impact of renewables generation on the level and volatility of prices, other results derived from the role of the other involved generation technologies have also been provided. The main conclusions can be summarized as follows.

Firstly, the picture has become much more informative when peak and off-peak hours are analyzed separately, confirming the fact that these price series should each be viewed as different commodities, with different features. Thereby, only when peak and off-peak prices are considered separately, do some changes that may be caused by renewables appear. Thus, for the period from 2002 to 2009, price volatility is higher and jumps are more frequent during peak hours, whereas during the last years of the sample, namely 2010–2013, where renewable generation is much more relevant, the opposite happens.

In line with the literature, there is a statistically negative relationship between the renewable generation share and the day-ahead market marginal prices. In addition, a significant relationship has been found between renewables generation share and the number of times that other technologies such as combined cycle, thermal and hydropower technology sets the marginal price. This relationship is negative only for the combined cycle technology. Therefore, it can be stated that renewables may be responsible for the replacement of CC as the technology setting marginal prices.

As well, we have obtained statistical confirmation of the fact that renewables generation share volatility is transferred to price volatility. However, significant positive relationships between the share volatility of other technologies (such as TER, HI, NUC and BG) and price volatility have been found and are worth being highlighted. Last but not least, this relationship becomes negative for the case of CC share, indicating that increases in this generation technology would contribute to reduce price volatility.

Lastly, in contrast to the general belief that the introduction of renewable generation would give rise to extreme (positive) prices, due to their intermittency and other supposed production planning and/or management problems, according to our results, increases in renewables generation share reduce the probability of upward jumps in peak prices, whereas no significant relationship between renewables generation share and jumps in off-peak prices have been found.

The results of this work can help practitioners and regulators understand how the inclusion of renewables into the electricity generation system has actually impacted the level and volatility of day-ahead market prices. One must be conscious of the fact that the intermittency of these sustainable generation technologies may be transferred to subsequent markets such as the intraday market. This issue, together with an analysis of the strategic bidding behaviour by the market participants when considering the transmission of information between the different markets and the information related to the foreseen generation by the different technologies, are left for further research.

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Appendix A

See Tables A1–A3 and Figs. A1–A3

Table A.1
Percentage of times each technology sets marginal price on average.
Included technologies are: hydraulic (HI), thermal (TER), combined cycle (CC), pumping hydropower (BG) and renewable (RE).

Year	Base-load hours (00:00–24:00)					Peak hours (08:00–20:00, business day)					Off-peak hours (00:00–08:00 and 20:00–24:00, business day, 00:00–24:00 holidays)				
	HI	TER	CC	BG	RE	HI	TER	CC	BG	RE	HI	TER	CC	BG	RE
2001	34.26	41.13	0,00	18.56	0,00	40.51	25.59	0.00	30.27	0.00	31.70	49.25	0.00	11.88	0.00
2002	42.2	37.31	0,00	17.34	0.25	58.92	12.11	0.00	29.40	0.20	34.38	49.97	0.00	10.81	0.27
2003	43.05	34.17	0,00	15.56	1.58	58.07	13.81	0.00	26.21	1.15	34.85	45.35	0.00	9.60	1.79
2004	27.41	34.26	14.57	18.09	1.78	35.49	15.78	12.94	29.18	1.47	23.02	43.75	16.06	11.74	1.92
2005	17.07	38.57	26.47	18.32	2.16	26.32	18.81	22.33	33.40	1.61	12.02	49.12	29.28	9.73	2.45
2006	26.35	32.76	39.33	5.1	4.84	17.83	23.34	29.81	8.27	7.01	31.19	37.11	43.61	3.18	3.65
2007	19.98	27.98	43.47	12.84	9.85	27.31	12.42	44.63	22.79	15.78	15.09	35.95	44.38	7.12	7.21
2008	21.19	22.17	48,00	10.11	3.96	30.70	15.98	43.98	16.08	5.66	14.89	25.33	52.02	6.44	3.14
2009	29.6	17.4	46.56	13.42	4.11	37.37	10.53	41.21	22.08	4.49	25.00	20.83	50.79	8.25	4.18
2010	42.45	15.63	32.64	19.06	9.55	44.98	9.45	23.56	30.28	6.14	40.57	18.24	39.03	12.36	11.13
2011	31.76	32.73	23.86	14.51	7.68	33.89	30.53	22.36	20.52	7.05	30.24	33.84	25.74	10.55	8.17
2012	32.32	30.77	15.69	15.32	12.84	37.81	27.34	12.62	20.88	12.02	28.55	33.32	18.07	11.53	13.35
2013	48.05	31.3	7.89	20.63	7.96	52.30	22.21	4.63	26.80	4.36	45.37	36.37	10.10	16.44	9.74

Table A.2
Marginal price descriptive statistics.
Descriptive statistics and outliers (in percentage) of the series of the Spanish day-ahead market marginal prices (2001–2013). Outliers have been identified following the procedure proposed by Benth et al. [14].

Year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Panel A) Base-load hours (00:00–24:00)													
Mean	30.13	37.40	28.96	27.94	53.68	50.53	39.35	64.43	36.96	37.01	49.92	47.24	44.26
Std Deviation	10.58	12.54	9.22	6.56	12.33	13.60	8.86	7.19	5.58	10.63	4.99	8.84	17.46
Skewness	0.53	1.34	0.26	0.72	0.40	1.02	1.25	−0.07	0.46	−1.08	−1.17	−1.37	−0.44
Kurtosis	−0.15	5.04	−0.97	−0.17	−0.30	0.72	1.97	−0.79	6.10	0.82	4.56	2.60	1.09
% Outliers	3.3%	4.7%	6.6%	0.3%	1.6%	0.5%	0.0%	0.0%	0.3%	5.8%	1.9%	5.2%	15.6%
% Outliers up	2.5%	3.0%	4.9%	0.3%	1.4%	0.3%	0.0%	0.0%	0.0%	3.6%	1.1%	3.0%	7.4%
% Outliers down	0.8%	1.6%	1.6%	0.0%	0.3%	0.3%	0.0%	0.0%	0.3%	2.2%	0.8%	2.2%	8.2%
Panel B) Peak hours (08:00–20:00, business day)													
Mean	37.41	47.07	36.30	33.16	67.04	61.72	46.52	71.12	40.40	42.20	54.51	53.30	51.20
Std Deviation	13.13	15.74	11.67	8.68	16.10	18.32	10.96	8.79	5.97	10.19	6.46	7.59	17.81
Skewness	0.38	1.96	−0.00	0.43	0.35	0.68	1.10	−0.07	0.53	−1.08	0.00	−1.55	−0.62
Kurtosis	−0.23	7.48	−1.23	−0.69	−0.47	−0.29	1.73	−0.75	9.16	1.26	3.38	4.56	1.96
% Outliers	3.5%	2.8%	9.4%	5.5%	4.7%	2.8%	0.0%	0.0%	0.8%	4.3%	0.8%	4.7%	13.8%
%Outliers up	1.6%	1.2%	4.7%	2.4%	2.0%	0.8%	0.0%	0.0%	0.0%	2.8%	0.4%	1.6%	6.3%
% Outliers down	2.0%	1.6%	4.7%	3.1%	2.8%	2.0%	0.0%	0.0%	0.8%	1.6%	0.4%	3.1%	7.5%
Panel C) Off−peak hours (00:00–08:00 and 20:00–24:00, business day, 00:00–24:00 holidays)													
Mean	26.50	32.86	25.48	25.34	46.77	44.61	35.11	60.31	34.83	34.21	47.35	44.33	40.83
Std Deviation	8.65	9.67	7.01	5.07	8.96	11.07	7.78	6.67	5.75	10.51	7.19	8.93	16.79
Skewness	0.44	0.85	0.28	0.86	0.58	1.18	1.30	−0.02	0.05	−0.97	−1.34	−1.19	−0.33
Kurtosis	−0.22	3.10	−0.57	0.36	0.36	1.06	1.60	−0.84	4.38	0.35	3.32	1.66	0.88
% Outliers	1.1%	1.4%	1.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.5%	6.3%	2.7%	4.9%	15.6%
% Outliers up	0.5%	0.5%	0.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	4.1%	1.6%	2.5%	7.1%
% Outliers down	0.5%	0.8%	0.8%	0.0%	0.0%	0.0%	0.0%	0.0%	0.5%	2.2%	1.1%	2.5%	8.5%

Table A.3
Day-ahead market production share of each technology.
Day-ahead market production share of each technology (daily average percentage).Included technologies are: renewable (RE), combined cycle (CC), hydraulic (HI), thermal (TER), nuclear (NUC) and pumping hydraulic generation (BG).

Year	Base-load hours (00:00–24:00)						Peak hours (08:00–20:00, business day)						Off-peak hours (00:00–08:00 and 20:00–24:00, business day, 00:00–24:00 holidays)					
	RE	CC	HI	TER	NUC	BG	RE	CC	HI	TER	NUC	BG	RE	CC	HI	TER	NUC	BG
2008	28.49	30.05	6.04	13.27	8.24	0.61	28.27	34.17	6.67	12.12	6.08	0.85	28.41	28.77	5.42	13.73	9.23	0.44
2009	40.35	26.44	7.65	10.57	6.66	1.27	40.03	29.79	7.38	9.50	5.36	1.67	39.71	25.76	7.61	11.19	7.31	1.00
2010	48,00	19.43	9.51	9.7	6.07	2.38	46.86	22.12	8.59	9.50	4.92	3.38	47.93	19.14	9.62	9.91	6.71	1.73
2011	51.93	13.99	6.14	14.8	6.54	2.86	49.95	16.01	6.01	15.66	5.43	3.77	52.55	13.62	6.03	14.47	7.13	2.23
2012	55.32	11.02	5.04	15.27	6.99	2.81	53.36	13.74	4.94	16.10	5.52	3.84	55.45	9.88	5.09	15.53	7.80	2.12
2013	58.93	6.7	7.87	13.95	6.56	2,00	58.98	7.53	7.76	14.99	4.72	2.56	58.27	6.47	7.89	13.95	7.46	1.64

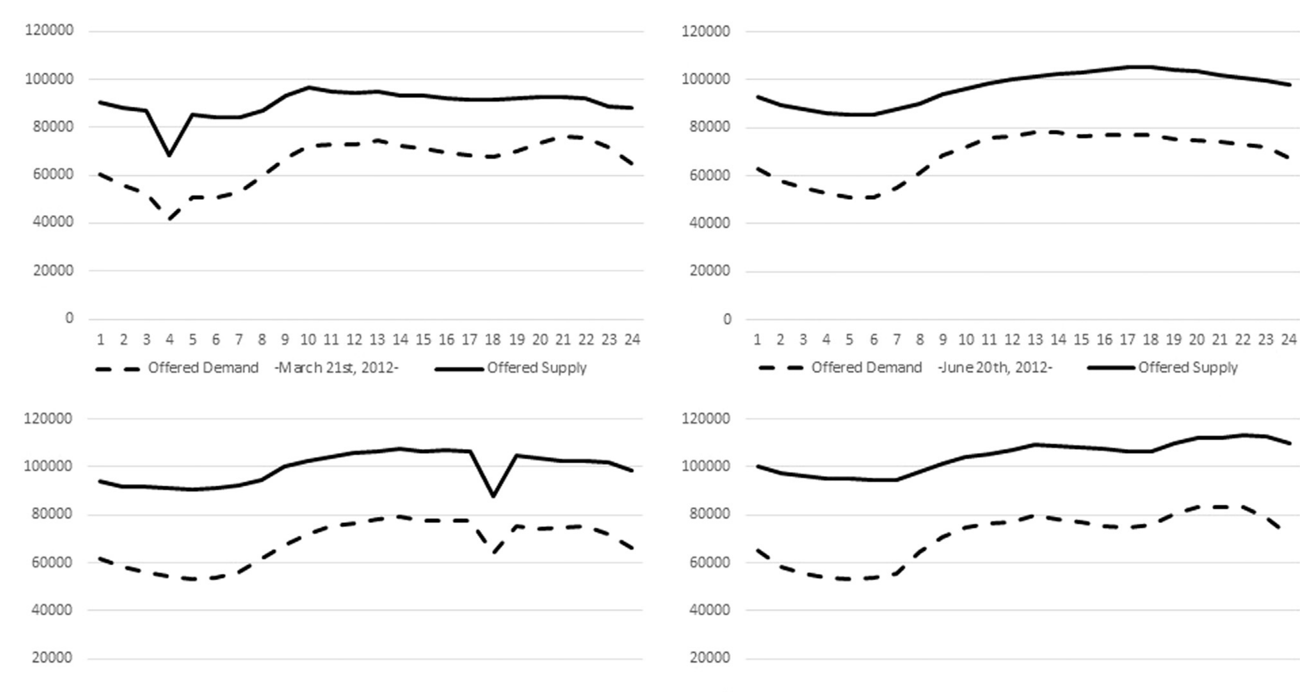

Fig. A.1. 24-h load curves of four typical days in 2012 (MWh).

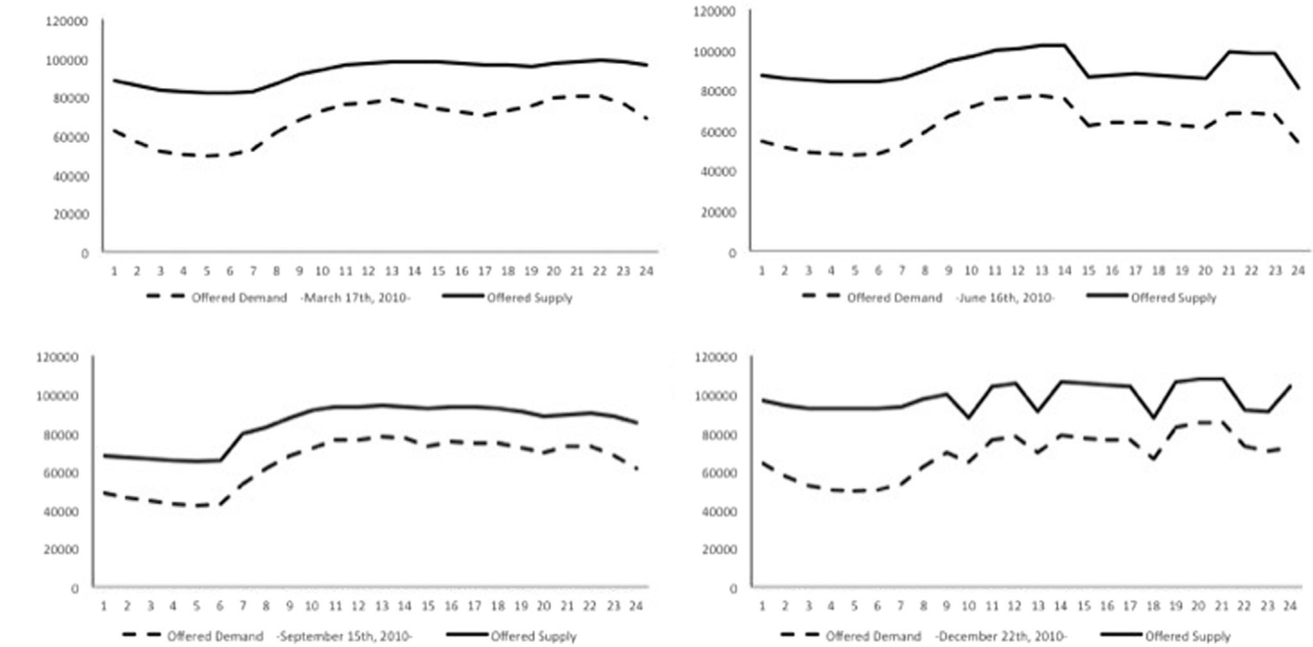

Fig. A.2. 24-h load curves of four typical days in 2010 (MWh).

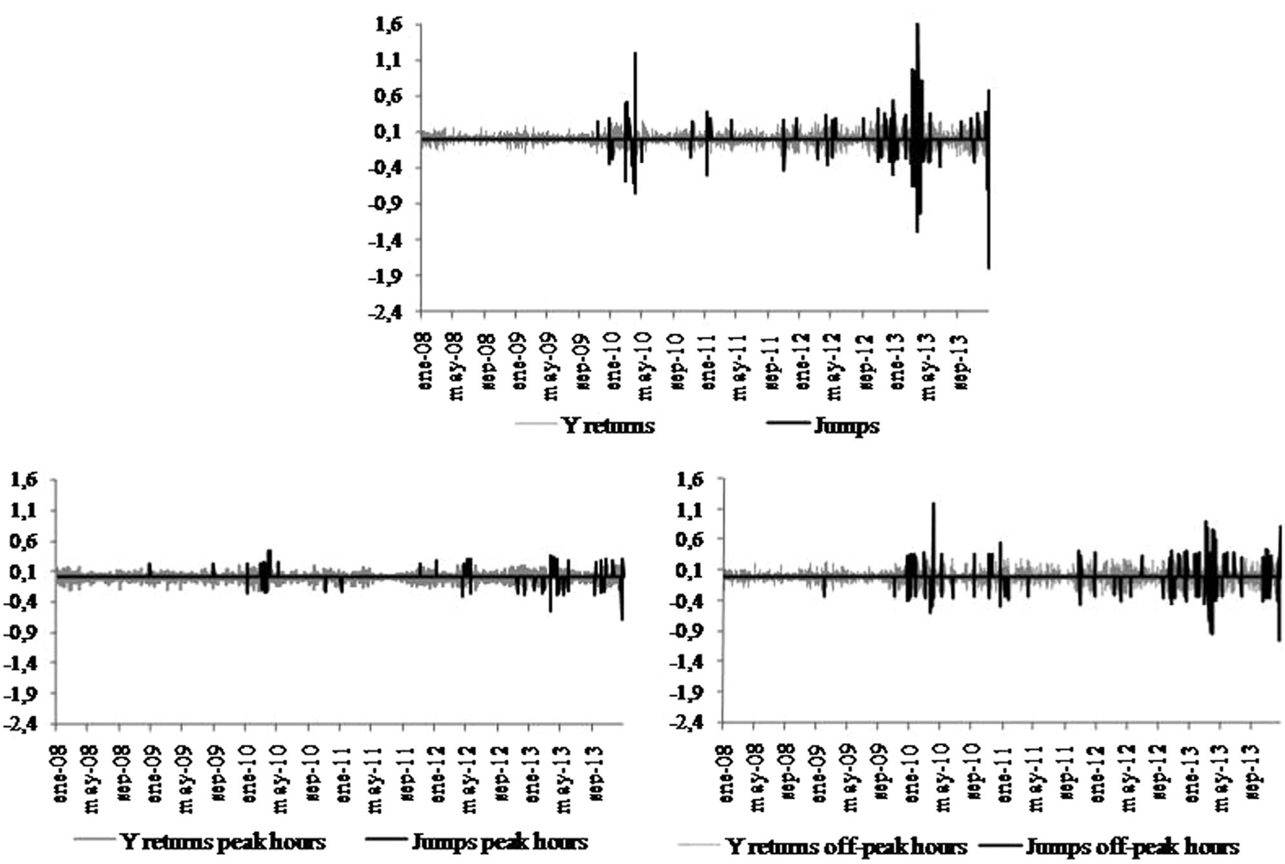

Fig. A.3. Price without seasonal component (*Y*) in returns and Jumps detected (2008–2013).

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