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Risk asymmetries in hydrothermal power generation markets

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ABSTRACT

Accurate decisions regarding exposure to and hedging against market risk, both of which are crucial for electricity producers and consumers, depend on a correct assessment of electricity price dynamics. This paper proposes a comprehensive empirical methodology to model price variations in electricity markets based on hydrothermal power generation. This proposal combines advances in time-series econometrics related to regime modeling, conditional heteroskedasticity, and extreme events. The study considers stylized facts of the series describing electricity prices, which are especially relevant for accurate risk pricing. More importantly, the proposed methodology enables the description and characterization of asymmetries at almost every level: intraday patterns, seasonal components, spikes, volatility regimes and extreme values; and the estimation of the effects of such asymmetries on traditional risk measures, such as VaR and CVaR. Different tail behaviors of positive and negative electricity returns are documented, which are relevant for assessing the risks of selling and buying strategies. In addition, asymmetries in risk that are conditional on the time at which the transaction occurs are found.

1. Introduction

Empirical literature has shown that electricity prices present several stylized facts, such as mean reversion, spikes, seasonal patterns, and long-range memory, among others Ref. [1]. Thus, modeling and forecasting these prices has become a challenge for academics and practitioners in the electricity industry. The importance of this exercise is indisputable in economic and financial terms, as decisions on selling and buying are a daily necessity for producers and consumers in the market. Needless to say, electricity is a main input for most economic activities in modern economies. Correct assessment of electricity price dynamics depends on accurate decisions about exposure to and hedging against market risk, both of which are crucial for electricity producers and consumers (household and real-sector firms).

For the aforementioned reasons, numerous approaches have been proposed in the empirical literature to model and forecast electricity prices. One approach is based on the techniques of time-series econometrics, such as exponential smoothing models or ARMA-GARCH models. Nevertheless, the literature has mainly ignored several asymmetries hidden in the process of price formation that are highly relevant for the agents involved in market transactions. There has been a consistent lack of studies providing a complete and coherent framework useful for quantifying market risk in electricity markets that take into account the whole set of documented stylized facts of electricity prices.

For example, some models are not sufficiently flexible to capture the different risks faced by consumers and producers in the market, which becomes evident from an independent estimation of tail parameters, scales, and thresholds at the lower and upper tails of the electricity return distributions. Some other models, working with daily data, ignore the idiosyncrasies of the stochastic processes describing the data at different times within a day. Such idiosyncrasies are important given the marked contrast in terms of electricity demand and power-generation alternatives depending on the hour at which an electricity transaction occurs. Finally, electricity prices are subject to weather conditions, which are known for their strong seasonal patterns and are by no means fully predictable. The latter is not properly recognized in a considerable branch of the empirical literature.

This paper aims to help fill this gap in the literature. It is argued that these asymmetries have important implications for risk measurement and modeling and, thus, for derivative pricing. Hence, it is sought to highlight and describe such asymmetries, and therefore contribute to the understanding of electricity price dynamics, which merit special consideration when modeling market risk in electricity markets. The description presented in this document of these asymmetries to assess the market risk that producers of electricity face in comparison to consumers is considered a novel approach. Currently, with new power-generation technolo-

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gies, consumers have gained a new role in the market—they can connect to the system and sell electricity—hence, there is a knowledge gap about the risk they face and how to manage it. This paper also contributes to the literature by measuring the market risk that agents face according to different transaction blocks within a day and by different volatility regimes.

The methodological approach lies within the reduced-form and statistical model groups, as characterized by Ref. [2]. On the one hand, reduced-form models are mainly inspired by traditional financial approaches, which are used to model stock prices, interest rates, and exchange rates. They aim to capture price dynamics rather than forecast them because these reduced-form models are mainly used for derivative pricing and hedging. On the other hand, statistical models are based on an econometric framework, particularly time-series analysis. Some approaches classified in this category are the similar-day method, exponential smoothing models, ARMA-GARCH models, threshold autoregressive models, and smooth-transition autoregressive models.

ARMA and seasonal ARMA approaches have frequently been used to fit the first moment of electricity prices, taking into account autocorrelation and seasonal patterns (e.g., Refs. [3,4]). Additionally, authors such as [5] estimate ARMA models with exogenous variables, like weather conditions and demand loads. They measure the effect of these variables on electricity prices. In addition, the literature has explored hybrid models that combine ARMA and computational intelligence models (see for example Ref. [6]). Regarding modeling and forecasting of demand loads, authors such as Ref. [7] have also used ARMA models, and furthermore, Ref. [8] have included seasonal cycles in a multi-timescale framework to enhance the forecast.

One main drawback of the ARMA-family models is that they assume a constant variance for the residuals. However, it is known that time series, such as electricity prices, tend to be characterized by conditional heteroskedasticity and volatility clustering. Thus, features regarding the series' second moments have been mainly addressed by generalized autoregressive conditional heteroskedasticity (GARCH) models Refs. [9–15].

The main disadvantage of traditional statistical models is their generally poor performance under the presence of spikes in the series. No clear consensus exists in the literature about whether spikes should be removed before estimation because removing or replacing them has direct effects on the model interpretation, for instance, in terms of the market's supply and demand shocks. Hence, Markov-switching models have been explored with the aim of adequately capturing spike regimes (see for example Refs. [16–20]). However, only Ref. [21] modeled electricity price volatility with Markov-switching GARCH models, as done here. This alternative explicitly addresses possible changes in the regime of electricity returns with unconditional volatilities, which are likely associated with changes in terms of weather conditions and unexpected demand and supply shocks.

With respect to the behavior of extreme negative or positive returns, which is also a target of this study, the closest antecedent is Ref. [22], who uses extreme value theory (EVT) with filtered data to analyze the risk faced by agents trading in the Nord Pool market. However, Ref. [22] focuses only on modeling one tail of the distribution, making it impossible to study possible asymmetries, such as the differences between the risk faced by consumers and producers, as pursued here. The author also does not study plausible switching behavior between volatility regimes.

Finally, unlike most of the studies referenced above, in this study, intraday electricity prices are used to capture as much information as possible from the price dynamics. Researchers such as Refs. [23,24] highlight the importance of using intraday data when modeling electricity prices. However, they do not include risk measurements in their studies, nor do they consider other

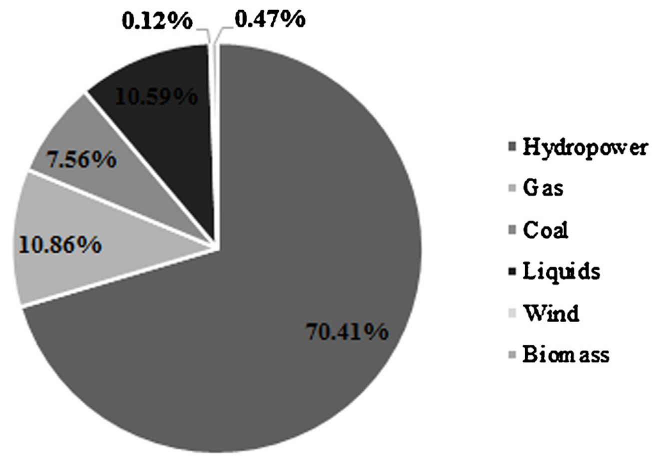

Fig. 1. Participation by technology in the power generation matrix.
Source: XM Information System

forms of asymmetries, such as (i) intraday patterns, (ii) seasonal components, (iii) spikes, (iv) volatility regimes, and (v) asymmetric extreme values (in terms of both shape and scale parameters).

In summary, none of the studies in the previous literature focus on highlighting the asymmetries that characterize electricity prices at almost every level, as done here. To illustrate the main message of the paper, the effects of such asymmetries on traditional risk measures, such as Value at Risk (VaR) and Conditional Value at Risk (CVaR), are also estimated, which are standard benchmarks in the industry. Thus, the objective is not to forecast or compare different modeling strategies; instead, it is to use a comprehensive methodology that allows for the description of several asymmetries hidden in the formation of electricity prices and to estimate their consequences in terms of risk for market agents. Table 1 presents a summary of the advantages and disadvantages of the main traditional methods used to model electricity prices. The proposed approach is a mixture of these methods in order to consider all of the features of electricity price dynamics.

In the empirical application, power-generation prices from the Colombian electricity market are used. This offers a unique opportunity to consider a market with heterogeneous power alternatives, and with a small capacity in terms of renewable-energy providers (which could act as smoothers of the volatility regimes, preventing dramatic changes in electricity prices). Colombia has an energy system based mostly on hydropower and thermal generation (see Fig. 1). Hydropower generation is the base of the system, while thermal generation is a backup technology for periods of high demand, or vulnerability in the hydric generation, due to the exposure to "El Niño", which decreases the levels of water reservoirs. Therefore, the costs of electricity generation are highly weather dependent in the short and long runs. Regarding renewable energy, its production is in an incipient phase. Producers are evaluating wind power-generation projects, and households are interested in solar power generation.

A hydro-thermal-based electricity market was selected for the empirical application because it presents large differences in the marginal costs of generation that depend on the type of technology used. This translates into prices characterized by spikes, seasonal patterns, and different volatility regimes, which make the proposal herein especially relevant in terms of risk measurement and management. Nevertheless, the empirical results of this document are of general interest.[1]

[1] According to International Energy Agency (IEA) statistics, in 2012, the following countries also had energy systems based on hydropower generation: Austria (63.7%),

Table 1
Summary of advantages and disadvantages of traditional modeling methods.

Method	References	Advantages	Disadvantages
ARMA and seasonal ARMA	[3–8]	Models the first moment (mean) of the price distribution taking into account autocorrelation and seasonal patterns	Assumes that residuals present constant variances (no heteroskedasticity or volatility clusters)
GARCH	[9–15]	Models the second moment (variance) of the price distribution considering conditional heteroskedasticity and volatility clustering	Poor performance in the presence of spikes
Markov-switching	[16–20]	Captures spike regimes in the first moment (mean) of the price distribution	Does not address explicitly possible regimes in the unconditional volatilities of the price distribution
Markov-switching GARCH	[21]	Captures changing regimes in the second moment (variance) of the price distribution	Does not model the tails of the price distribution
Extreme value theory	[22]	Models the tails of the distribution (extreme negative or extreme positive prices returns)	Does not consider the effect of the third moment (bias) of the price distribution
Intraday models	[23,24]	Are used to capture as much information as possible from the price dynamics	High computational time

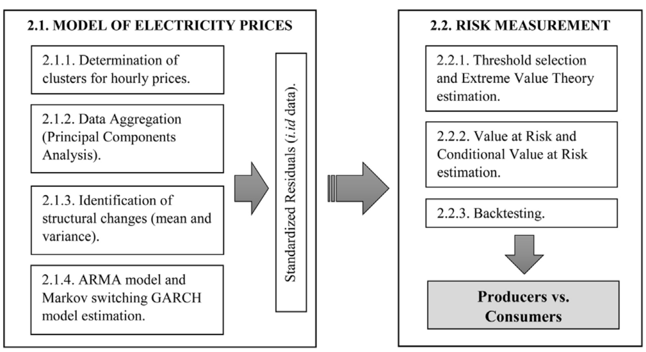

Fig. 2. Flow diagram of the proposed methodology.

2. Methodology

A methodology to assess risk asymmetries in hydrothermal-based electricity markets that is possibly applicable to other electricity markets is proposed. The methodology consists of two parts: first, modeling the dynamics of electricity prices to forecast the first two moments of the distribution of electricity returns; second, measuring the risks faced by electricity producers and consumers according to VaR and CVaR statistics (Fig. 2). The implementation includes discriminating among different time zones within a day and different volatility regimes during a given year.

2.1. Model of electricity prices

2.1.1. Determination of clusters

Power-generation prices are formed each hour of the day; in some markets, several hours present similar prices. Hence, the first step of the proposed methodology is to determine how hourly prices cluster, as in the method proposed by Ref. [15]. The k-means method is applied, which divides the data into k groups such that each datum is assigned to the group with the nearest mean. The algorithm used is the one proposed by Ref. [25].

2.1.2. Data aggregation

Once hourly prices are divided into blocks, it is necessary to aggregate them into one price per block for each day. The first option is to take the average of the prices within the same block. However, this option does not take into account the variability of the prices within the same block. Therefore, the use of principal component analysis (PCA) to aggregate the prices in each block is proposed. Additionally, PCA is a well-known alternative for estimating dynamic factor models (DFMs) among practitioners and academics. DFMs assume a covariation among the time series that can be summarized by a few underlying unobserved factors (see Refs. [26–28]).

The first principal component of the price returns per block is selected. This single statistic seems to capture most of the volatility within each block.

2.1.3. Identification of structural changes

After aggregating the hourly price returns for each block, it is identified whether each series has structural changes in either the mean or the variance. If structural changes are identified, the use of Markov-switching models is proposed. To test structural changes in the mean of the returns for each block, the sequential test proposed by Ref. [29] is used. This test is only suited for the mean of the distribution. Thus, to test structural changes in the variance, the score-based CUSUM test presented in Ref. [30] is used.

2.1.4. ARMA and MS-GARCH model estimation

Ref. [31] introduced Markov-switching (MS) models in econometrics. This type of model assumes that the evolution of a time series depends on the realizations of a hidden Markov chain with a set of states of the world. Ref. [32] extended the approach to a model that combines autoregressive conditional heteroskedasticity (ARCH) models, proposed by Refs. [33,34] with an MS model. Refs. [35–37] proposed a generalization of the [32] SW-ARCH model to a Markov-switching generalized autoregressive conditional heteroskedasticity (MS-GARCH) model.

Estimating the first and second moments of electricity price returns using an ARMA model and an MS-GARCH model, respectively, is proposed. As previously mentioned, this strategy allows for the identification of possible changes in the unconditional return distribution of electricity prices, possibly due to changes in weather conditions or exogenous demand and supply shocks.

First, the methodology of Ref. [38] to estimate an ARMA model for each block of electricity price returns is followed. Let $\{X_t\}$ be the time series of the returns of each block; then, the ARMA (p,q) model of X_t can be expressed as

$$X_t = \alpha_0 + \sum\nolimits_{i=1}^{p} \alpha_i X_{t-i} + \sum\nolimits_{i=0}^{q} \beta_i \varepsilon_{t-i} . \quad (1)$$

Second, the residuals $\{\varepsilon_t\}$ from the estimation of Eq. (1) are modeled with the MS-GARCH method proposed by Ref. [37]. Unlike the methods proposed by Refs. [35,36], this method has the advantage

Brazil (75.2%), Costa Rica (71.1%), Ecuador (53.6%), Guatemala (47.4%), Iceland (70.3%), Korean Democratic Republic (70.2%), Latvia (60.1%), New Zealand (51.7%), Norway (96.7%), Paraguay (100%), Peru (53.5%), Sweden (47.4%), and Switzerland (56.6%).

of allowing the regime variances to depend on past shocks and past variances, such as in the case of GARCH models without regimes.

Following Ref. [37], let the residuals $\{\varepsilon_t\}$ equal $\varepsilon_t = \eta_t \sigma_{\Delta t,t}$, where η_t is a white-noise process and $\{\Delta_t\}$ is a Markov chain with state space equal to $S = \{1, \ldots, k\}$; P is a kxk transition matrix, where the element $p_{ij} = P[\Delta_t = j | \Delta_{t-1} = i]$. The variances for the k regimes follow Eq. (2):

$$\sigma_{st}^2 = \alpha_{s0} + \alpha_{s1}\varepsilon_{t-1}^2 + \beta_s \sigma_{st-1}^2 \text{ for } s = \{1, \ldots, k\} \tag{2}$$

where $\alpha_{s0} > 0$ and $\alpha_{s1}, \beta_s \geq 0$.

In the case of a two-state Markov chain, the transition matrix is equal to

$$\begin{pmatrix} P_{11} & P_{21} \\ P_{12} & P_{22} \end{pmatrix}. \tag{3}$$

Following Ref. [39], if the Markov chain does not have absorbent states, that is, $P_{11} < 1$ and $P_{22} < 1$, the transition matrix is irreducible. In addition, the Markov chain is ergodic if $P_{11} < 1$, $P_{22} < 1$, and $P_{11} + P_{22} > 0$.

The standardized residuals obtained from estimating Eqs. (1) and (2) must be i.i.d. to properly estimate the EVT parameters.

2.2. Risk measurement

2.2.1. Threshold selection and EVT estimation

The Peak Over Threshold (POT) method is used to estimate the parameters that describe the tails of the distribution of the standardized residuals.

Following Ref. [40], the POT methodology suggests that extreme observations over a certain threshold, that is, returns that are in the tails, follow a generalized Pareto distribution (GPD), as described in Eq. (4) (according to Refs. [41,42]):

$$G_{\xi,\beta}(\boldsymbol{x}) = \begin{cases} 1 - \left(1 + \xi \boldsymbol{x}/\beta\right)^{-1/\xi} & if \quad \xi \neq 0 \\ 1 - exp\left(-\boldsymbol{x}/\beta\right) & if \quad \xi = 0 \end{cases}, \tag{4}$$

where β is a scale parameter, ξ is a shape parameter, and $x = z_i - \nu_i$, for which z_i are the standardized residuals obtained from Eqs. (1) and (2) and ν_i is the chosen threshold.

If $\xi = 0$, the tail follows an exponential distribution; if $\xi < 0$, the tail follows a Pareto type II distribution that is characterized by being short-tailed; and if $\xi > 0$, the tail follows an ordinary Pareto distribution with heavy tails.

In the empirical implementation of this document, the threshold was selected to be between 85% and 97% such that the estimated parameters of scale and shape were significant and corresponded to the area of the Hill plot, where the plot of $\alpha = 1/\xi$ stabilizes against different thresholds. The Hill estimator is only defined for the ordinary Pareto distribution, i.e., when $\xi > 0$ (see Ref. [43]).

2.2.2. VaR and CVaR estimation

Theoretically, the VaR is a measure of the maximum expected loss of a portfolio of assets in a given period at a given confidence level $(1-\alpha)$ (see Ref. [44]). The CVaR is the expected loss if an extreme event actually occurs, beyond the confidence level of the VaR, in the tails of the distribution. Following Ref. [45], the VaR and CVaR with EVT estimations are

$$VaR_{(1-\alpha)} = q_{1-\alpha}(Z) = \nu + \frac{\beta}{\xi}\left[\left(\frac{1-\alpha}{T_\nu/T}\right)^{-\xi} - 1\right], \tag{5}$$

$$CVaR_{(1-\alpha)} = \frac{VaR_{(1-\alpha)}}{1-\xi} + \frac{\beta - \xi\nu}{1-\xi}, \tag{6}$$

where $(1-\alpha)$ is the confidence level, ν is the threshold, β is the scale parameter, ξ is the shape parameter, T is the total number of data values, and T_ν is the number of extreme observations.

With this method of estimating the VaR and CVaR, these indicators measure two types of financial risk: one related to the kurtosis of the distribution (the heaviness of the tails) through the EVT parameters, and one related to the skewness of the distribution, through the threshold ν.

The VaR and CVaR conditional on time are

$$VaR_{(1-\alpha)}^t = \mu_{t+1} + \sigma_{t+1}\, q_{1-\alpha}(Z), \tag{7}$$

$$CVaR_{(1-\alpha)}^t = \mu_{t+1} + \sigma_{t+1}\, ES_{(1-\alpha)}, \tag{8}$$

where μ_{t+1} is the mean forecast and σ_{t+1} is the variance forecast estimated by Eqs. (1) and (2).

2.2.3. Backtesting

Following Ref. [46], the $VaR_{(1-\alpha)}^t$ promises that the standardized residuals $\{Z\}$ will only overpass the risk measure forecast α*100% of the time. If a residual is higher than the VaR, this is considered a violation or an exceedance. Therefore, the hit sequence of VaR violations or exceedances is

$$I_{t+1} = \begin{cases} 1 & if \ z_{t+1} < -VaR_{(1-\alpha)}^t \\ 0 & if \ z_{t+1} > -VaR_{(1-\alpha)}^t \end{cases} for \quad t = 1, \ldots, T. \tag{9}$$

The likelihood-ratio test in Eq. (10) is used to prove whether the proportion of violations obtained by the VaR model is significantly different from the promised proportion α:

$$LR_{uc} = -2ln\left[\frac{(1-\alpha)^{T_0}\alpha^{T_1}}{\left(1 - T_1/T\right)^{T_0}\left(T_1/T\right)^{T_1}}\right] \sim \chi_1^2, \tag{10}$$

where T is the total number of observations in $\{Z\}$, and T_0 and T_1 are the numbers of 0s and 1s in the hit sequence I_{t+1}, respectively. This test is known as the unconditional coverage test because it only tests if the VaR exceeds the standardized residuals the correct number of times. However, it is also important to assess if the exceedances cluster or not by means of an independence test. The independence test determines if the violations cluster or if they are independent throughout the hit sequence. The likelihood-ratio test is equal to

$$LR_{ind} = -2ln\left[\frac{\left(1 - T_1/T\right)^{T_0}\left(T_1/T\right)^{T_1}}{(1-\pi_{01})^{T_{00}}\pi_{01}^{T_{01}}(1-\pi_{11})^{T_{10}}\pi_{11}^{T_{11}}}\right] \sim \chi_1^2, \tag{11}$$

where $\pi_{01} = T_{01}/(T_{00} + T_{01})$; $\pi_{11} = T_{11}/(T_{10} + T_{11})$; $\pi_{00} = 1 - \pi_{01}$; $\pi_{10} = 1 - \pi_{11}$. T_{00} is the number of non-violations followed by a non-violation; T_{01} is the number of non-violations followed by a violation; T_{10} is the number of violations followed by a non-violation; and T_{11} is the number of violations followed by a violation.

The conditional coverage test assesses simultaneously if the VaR exceedances are independent and if the proportion of exceedances is equal to the expected one. The test statistic is equal to

$$LR_{cc} = LR_{uc} + LR_{ind}. \tag{12}$$

The independence test presented above has power against first-order Markov-structure dependence. To take into account more general forms of dependence, Ref. [47] developed a test based on the duration of time between the VaR's violations. In the test, the no-hit duration sequence is equal to

$$D_i = t_i - t_{i-1}, \forall i, \tag{13}$$

Table 2
Descriptive statistics of electricity prices.

	Block 1 (23–7)	Block 2 (8–17; 21–22)	Block 3 (18–20)
Mean	110.93	132.54	154.75
Median	110.59	127.88	148.44
Maximum	396.09	435.86	445.02
Minimum	33.366	35.471	36.785
Std. Dev.	55.481	61.670	64.786
Skewness	0.7631	1.0828	1.0258
Kurtosis	4.0853	5.2554	4.9796
Observations	1820	1820	1820

Block 1 corresponds to the hours between 23:00 and 07:00 of the next day.

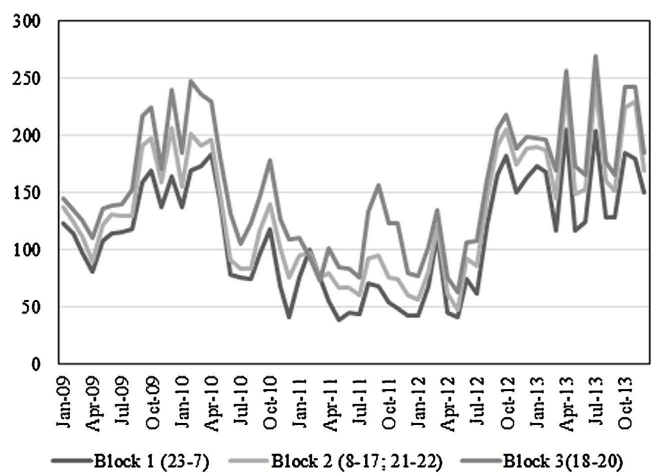

Fig. 3. Average behavior of monthly electricity prices.
Block 1 corresponds to the hours between 23:00 and 7:00 of the next day.

where t_i denotes the day of violation i. If the model is correctly specified, the sequence should be memoryless. To test model specification, Ref. [47] use the Weibull distribution, which has a hazard function with a closed form:

$$\lambda_W(D) = a^b b D^{b-1}\,. \tag{14}$$

Under the null hypothesis, $b = 1$, which is a special case where the Weibull distribution's hazard function takes the form of the Exponential distribution. Under the alternative hypothesis, $b < 1$ and the hazard function presents excessive short or long durations. The short durations correspond to very volatile periods, and the long durations to relatively calm periods. Hence, if the null hypothesis is rejected, the risk model has an incorrect volatility and dependence structure specification.

3. Empirical results and discussion

The proposed methodology is applied to the Colombian market because of data availability and the previously mentioned characteristics of this market. The data were obtained from the XM platform, the operator of the National Interconnected System and the administrator of the Colombian Wholesale Energy Market. The frequency of the data is hourly, and the sample period starts on January 1, 2009, and ends on December 31, 2013.

Using the proposed cluster analysis, it is found that the hourly electricity prices for the Colombian market during this period clustered around three time blocks: the first block of hours spans from 23:00 to 07:00 of the next day; the second block spans from 08:00 to 17:00, and 21:00 to 22:00; and the third block spans from 18:00 to 20:00. Table 2 and Fig. 3 show that Block 3 presents the highest prices and variability over the whole sample, while Block 1 presents the lowest prices and variability. This is due to different demand charges applied during the day; for instance, the hours in Block 3 correspond to peak hours when consumption is the highest. Although Block 2 does not present the highest prices, it incorporates 12 h of transactions and presents the highest bias and kurtosis.

After determining how hourly prices cluster in the sample period, the price returns are obtained and aggregated through PCA. As a result, each block corresponds to a single price return per day. This price return aggregates most of the variability of the original hourly prices within the block. The percentage of variation explained by the first principal component is 66.63% for Block 1, 69.42% for Block 2, and 68.89% for Block 3.

Table 3
Properties of the estimated GARCH models.

Block 1				
Model	**N**	**L***	**AIC**	**BIC**
Gaussian GARCH(1,1)	4	−1,390.05	2,788.11	2,810.13
Student t GARCH(1,1)	5	**−1,024.93**	**2,059.87**	**2,087.40**
Block 2				
Model	**N**	**L***	**AIC**	**BIC**
Gaussian GARCH(1,1)	4	−1,456.43	2,920.85	2,942.88
Student t GARCH(1,1)	5	−1,279.27	2,568.54	**2,596.07**
Gaussian SWG(2)	10	−1,287.68	2,595.35	2,650.41
Student t SWG(2)	12	−1,266.97	**2,557.94**	2,624.01
Gaussian SWG(3)	18	−1,268.97	2,573.93	2,673.04
Student t SWG(3)	21	**−1,260.18**	2,562.36	2,677.99
Block 3				
Model	**N**	**L***	**AIC**	**BIC**
Gaussian GARCH(1,1)	4	−1,490.62	2,989.23	3,011.26
Student t GARCH(1,1)	5	−1,394.12	2,798.25	**2,825.78**
Gaussian SWG(2)	10	−1,390.22	2,800.44	2,855.50
Student t SWG(2)	12	−1,379.19	**2,782.39**	2,848.46
Gaussian SWG(3)	18	**−1,373.71**	2,783.42	2,882.53
Student t SWG(3)	21	−1,375.49	2,792.98	2,908.61

For Blocks 2 and 3, six different models were estimated, including Markov-switching models with two and three regimes. Column N reports the number of parameters of the model, which includes three GARCH parameters and initial variance estimation for each regime, the probabilities of being in a regime and, in the case of the Student *t* models, the estimation of the degrees of freedom. Column L^* reports the Log-Likelihood; columns AIC and BIC report the Akaike Information Criterion and the Bayesian Information Criterion, respectively, and are equal to: $AIC = -2L^* + 2N$; $BIC = -2L^* + N\log(T)$. The best model, according to each criterion, is presented in boldface. The models highlighted in gray are the selected models. For Blocks 2 and 3, the selection was made according to the model that presented the lowest AIC because not having an under-fitted model is preferred. For Block 1, the Student *t* GARCH (1,1) model was not selected, which is the best according to all of the selection criteria, because it is not stationary.

Next, the price returns for each block are tested for the presence of structural changes. The sequential test by Ref. [29] indicates that the series do not present breaks in the first moment of the distribution during the study sample. However, the score-based CUSUM test indicates that Blocks 2 and 3 present breaks in the variance.

Given that the variances for Blocks 2 and 3 show evidence of structural changes, the second moments of their distributions are modeled using MS-GARCH (1,1) models, while Block 1 is modeled with a standard GARCH (1,1)[2] model. Following the proposed methodology, the first moments of the distributions are fitted to an ARMA model, and it is determined that an ARMA (1,1) model has the best fit for Block 1. For Blocks 2 and 3, the best fit is an ARMA (7,7) model, which captures seasonal patterns in the prices.[3]

Table 3 shows the properties of the estimated GARCH models. For Blocks 2 and 3, models with one, two, and three regimes are estimated, with residuals having Gaussian and Student's *t* distributions. For these two blocks, the Student *t* GARCH (1,1) model with

[2] An MS model in the mean of the return distribution of each block was also estimated. However, the regimes in this case are not statistically significant. The results are available upon request.

[3] The ARMA model that best fits each block was selected following the methodology of Ref. [38]. We used an optimal number of lags such that the residuals are not autocorrelated, and to avoid biases in the estimation of the parameters.

Table 4
Parameter estimates for selected GARCH models.

k	α_{s0}	α_{s1}	β_s	$\alpha_{s1}+\beta_s$	$\alpha_{s1}/\left(1-\beta_s\right)$	% time in k
Block 1						
1	0.1247	0.4438	0.2491	0.6929	0.5910	100%
Block 2						
LV	0.0174	0.3848	0.5961	0.9809	0.9528	73%
HV	0.0008	0.0345	0.9706	1.0051	1.1750	27%
Block 3						
LV	0.0253	0.2456	0.5972	0.8429	0.6098	53%
HV	0.0003	0.0522	0.9622	1.0144	1.3812	47%

Column k reports the different regimes; for Block 1, only one regime was estimated, while for Blocks 2 and 3, two regimes were estimated. The acronyms LV and HV represent a low-volatility regime and high-volatility regime, respectively. The column that reports the percentage of time that the model is in each regime was calculated according to the number of times the returns had a probability of being in that specific regime of more than 0.5. The standardized residuals obtained from these models passed all the specification tests (Ljung-Box Q test and LM test); hence, they are i.i.d. data and proper input for the EVT estimation.

Table 5
Transition matrices.

Block 2		Block 3	
State 1	State 2	State 1	State 2
0.9000	0.3021	0.6986	0.3129
0.1000	0.6979	0.3014	0.6871

State 1 corresponds to the low-volatility regime, and state 2 corresponds to the high-volatility regime.

two regimes is selected as the model with the best fit. For Block 1, the Gaussian GARCH (1,1) model is selected.

Table 4 presents the parameter estimates for the selected models. For Blocks 2 and 3, one of the variance regimes estimated corresponds to a high-volatility regime and the other to a low-volatility regime. For both cases, the GARCH (1,1) model of the high-volatility regime is not stationary given that $\alpha_1 + \beta_1 \approx 1$, which corresponds to an IGARCH model that presents persistent changes in the volatility. This result agrees with the long-memory feature of electricity prices because one shock in the variance would be persistent in time. However, this does not imply that shocks never fade in the model because the variance always returns to the low-volatility regime, which is stationary. Therefore, the variance does not explode, despite the parameter estimates of the high-volatility regime; on the contrary, it always regulates by returning to the low-volatility regime. In other words, the transition probabilities between the regimes configure an ergodic Markov chain, hence $P_{11} < 1$, $P_{22} < 1$, and $P_{11} + P_{22} > 0$ for each block (see Table 5).

Furthermore, $\alpha_{s1}/(1-\beta_s)$ measures the total impact of a shock to the future variance regime. Block 3 not only presents the highest impact of shocks to its high-volatility regime but also remains in this regime 47% of the time, while Block 2 remains in the high-volatility regime only 27% of the time. Thus, Block 3 presents the highest prices and the highest volatility, and the model remains in this regime for the longest period. This high-volatility behavior can be explained by a characteristic of hydrothermal-based markets: when electricity demand increases, all generation technologies must produce to meet demand. Thus, thermal plants must start after the hydropower plants cannot meet the demand, and they may present marginal costs of up to 300% higher than those of hydropower plants.

Figs. 4 and 5 plot the price returns for each block against the probability of being in the high-volatility regime; being in this regime coincides with clusters of high volatility in the price returns.

After modeling the first and second moments of electricity-price return distributions and obtaining i.i.d. standardized residuals, the upper and lower tails of these distributions are modeled. Upper tails represent the extreme risk values encountered by electricity consumers, while lower tails represent the risk faced by producers. For all thresholds, the shape parameter is positive, indicating that all of the distributions are heavy tailed.[4]

Table 6 shows a mean-difference test for the shape-parameter estimates in each block to determine whether the tails within blocks are asymmetric in terms of heaviness. For Blocks 1 and 2, the lower tail is statistically heavier than the upper tail, which means that producers face a higher concentration of extreme events than consumers. For the combined regime of Block 3, the mean of the shape-parameter estimates of the lower tail is also statistically higher than the upper-tail parameter estimates; the high-volatility regime exhibits the opposite behavior, and the tails of the low-volatility regime are not significantly different.

With the EVT parameter estimates, the VaR and CVaR conditional to the mean and variance forecasts for each day in the sample are estimated. In Figs. 6 and 7, the estimations of the VaR and the CVaR, respectively, are presented. For Block 1, the risk measures indicate that the risk level faced by producers (lower tail) tends to be higher than the risk level faced by consumers (upper tail). Conversely, for Blocks 2 and 3, the risk faced by buyers tends to be higher than the risk faced by sellers. Comparing the latter results with those of the mean-difference tests for the tail param-

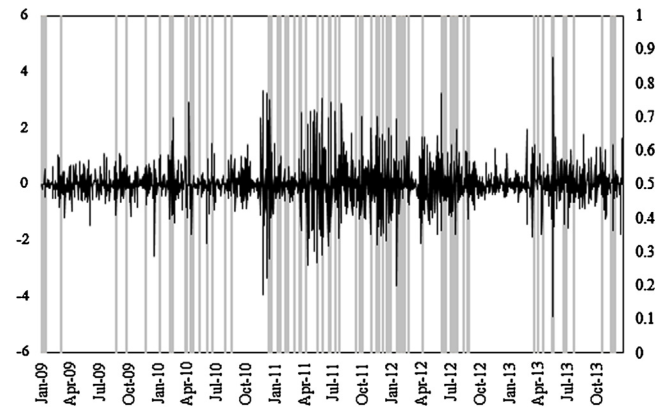

Fig. 4. High-volatility regime probabilities and price returns: Block 2.
The gray lines correspond to the periods in which the GARCH model is in the high-volatility regime with a probability of more than 0.7.

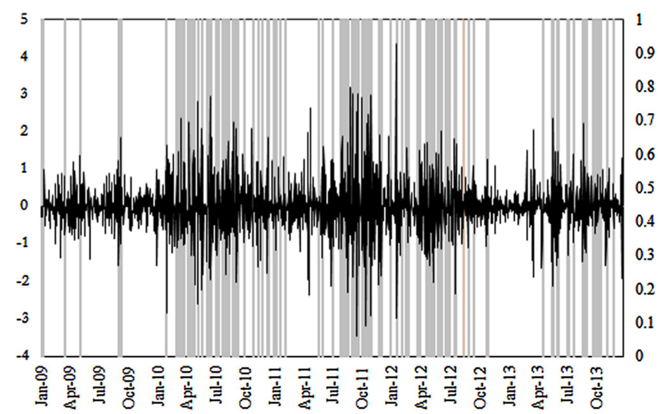

Fig. 5. High-volatility regime probabilities and price returns: Block 3.
The gray lines correspond to the periods in which the GARCH model is in the high-volatility regime, with a probability of more than 0.7.

[4] The results from the estimation of the shape and tail parameters for each block and for each tail are available upon request.

Table 6
Mean difference tests for shape parameter estimates.

	Upper tail		Lower tail		Lower tail – Upper tail	
	Mean (shape)	Standard deviation	Mean (shape)	Standard deviation	Mean difference	t Statistic
Block 1	0.1560	0.0576	0.2056	0.0551	0.0496	2.4098**
Block 2	0.1236	0.0416	0.2802	0.0439	0.1566	10.03***
High-volatility regime	0.1798	0.0518	0.2411	0.0354	0.0613	3.782***
Low-volatility regime	0.0892	0.0563	0.2686	0.0331	0.1795	10.65***
Block 3	0.0897	0.0357	0.1081	0.0386	0.0184	1.3563*
High-volatility regime	0.1691	0.0379	0.0389	0.1054	−0.1301	−4.50***
Low-volatility regime	0.0916	0.0455	0.0909	0.0929	−0.0006	−0.0236

Block 2 and Block 3 estimations were performed using the ARMA model residuals standardized by the average volatility from the high-volatility and low-volatility regimes. The residuals from the ARMA model were also standardized with only the variance of the high-volatility regime or the low-volatility regime.
* Significant at a confidence level of 90%.
** Significant at a confidence level of 95%.
*** Significant at a confidence level of 99%.

Table 7
Unconditional and conditional coverage Value at Risk exceedances test.

Upper tail						
	Expected exceedances	Actual exceedances	uc.LRp	uc.Decision	cc.LRp	cc.Decision
Block 1	90	116	0.0093	Reject H0	0.0009	Reject H0
Block 2	90	109	0.0579	Fail to reject H0	0.1392	Fail to reject H0
Block 2 — HV	90	108	0.0727	Fail to reject H0	0.1179	Fail to reject H0
Block 2 — LV	90	92	0.9017	Fail to reject H0	0.8146	Fail to reject H0
Block 3	90	109	0.0579	Fail to reject H0	0.0668	Fail to reject H0
Block 3 — HV	90	90	0.9270	Fail to reject H0	0.0198	Fail to reject H0
Block 3 — LV	90	98	0.4470	Fail to reject H0	0.7423	Fail to reject H0
Lower tail						
	Expected exceedances	Actual exceedances	uc.LRp	uc.Decision	cc.LRp	cc.Decision
Block 1	90	97	0.5124	Fail to reject H0	0.0002	Reject H0
Block 2	90	106	0.1117	Fail to reject H0	0.0486	Fail to reject H0
Block 2 — HV	90	99	0.3869	Fail to reject H0	0.1136	Fail to reject H0
Block 2 — LV	90	93	0.8176	Fail to reject H0	0.1774	Fail to reject H0
Block 3	90	112	0.0278	Fail to reject H0	0.0140	Fail to reject H0
Block 3 — HV	90	99	0.3869	Fail to reject H0	0.3696	Fail to reject H0
Block 3 — LV	90	82	0.3331	Fail to reject H0	0.0758	Fail to reject H0

Column uc.LRp reports the unconditional coverage test p-value, and uc.Decision the unconditional coverage test decision on the null hypothesis (H0) given the confidence level. The unconditional coverage H0 states that the VaR presents the correct number of exceedances. Column cc.LRp reports the conditional coverage test p-value, and cc.Decision the conditional coverage test decision on the H0 given the confidence level. The conditional coverage H0 states that the VaR presents the correct number of exceedances and are independent. The acronyms LV and HV represent the low-volatility regime and high-volatility regime, respectively.

eters (Table 6), it can be highlighted, as stated in the methodology, that the risk faced by the agents, measured with VaR and CVaR, depends not only on the concentration of extreme events in the tails (kurtosis) but also on the threshold (bias).

Although Block 3 remains in the high-volatility regime longer than Block 2, the latter presents higher VaR and CVaR estimations. This can be explained by the fact that the impact of a shock to the variance of the low-volatility regime of Block 2 is 56% higher than the impact for Block 3. Hence, Block 2 is the riskiest of the blocks, a result that coincides with the fact that the prices of this block present the highest bias and kurtosis.

Figs. 8 and 9 present a specific case of the VaR and CVaR estimations to further illustrate the implications of the proposed methodology in terms of risk management. The risks faced by consumers and producers differ across blocks of demand and variance regimes. Hence, this methodology allows for the consideration of risk measurements for producers and consumers separately, taking into account the different volatility regimes in different blocks that depend on demand charges. These risk measurements are important inputs for the negotiation of selling and buying contracts of electricity as well as for the valuation of derivatives.

For this specific case, all of the blocks are above a 45° line starting at the origin, which means that all of the CVaR estimates are higher than the estimates of these measures with a normal distribution. Moreover, for all blocks, the risk faced by electricity sellers (lower tail) is higher than the risk faced by buyers (upper tail) in terms of the VaR. However, the CVaR values are very similar for both tails.

Fig. 9 presents the CVaR and VaR ratio for this example, which measures the relative distance between the two risk measures. This ratio provides additional information about the risks faced by buyers and sellers through the different blocks of transaction and volatility regimes. The ratio measures the blocks and regimes that are more exposed to extreme losses, which are underestimated by the VaR. In this case, buyers face a higher risk if an extreme event actually occurs.

Finally, Tables 7 and 8 present the backtesting results for all of the VaR estimations using three different tests: unconditional and conditional coverage tests, and duration test. The model shows a remarkably good fit to the data and performs well when predicting risk.[5] Figs. 10 and 11 plot the unconditional coverage test. They

[5] Backtesting comparisons of the proposed methodology with other available in the literature were performed. Specifically, the alternative methods used were: ARMA-GARCH, historical simulation, and ARMA-GARCH Montecarlo simulation (see Ref. [40] for details about each method). The backtesting results are presented in the Appendix A. The test used is the Value at Risk duration test, proposed by Ref. [47] that, unlike the independence test proposed by Ref. [46], has power against first and higher orders Markov structures. The alternative VaR estimations have a poor

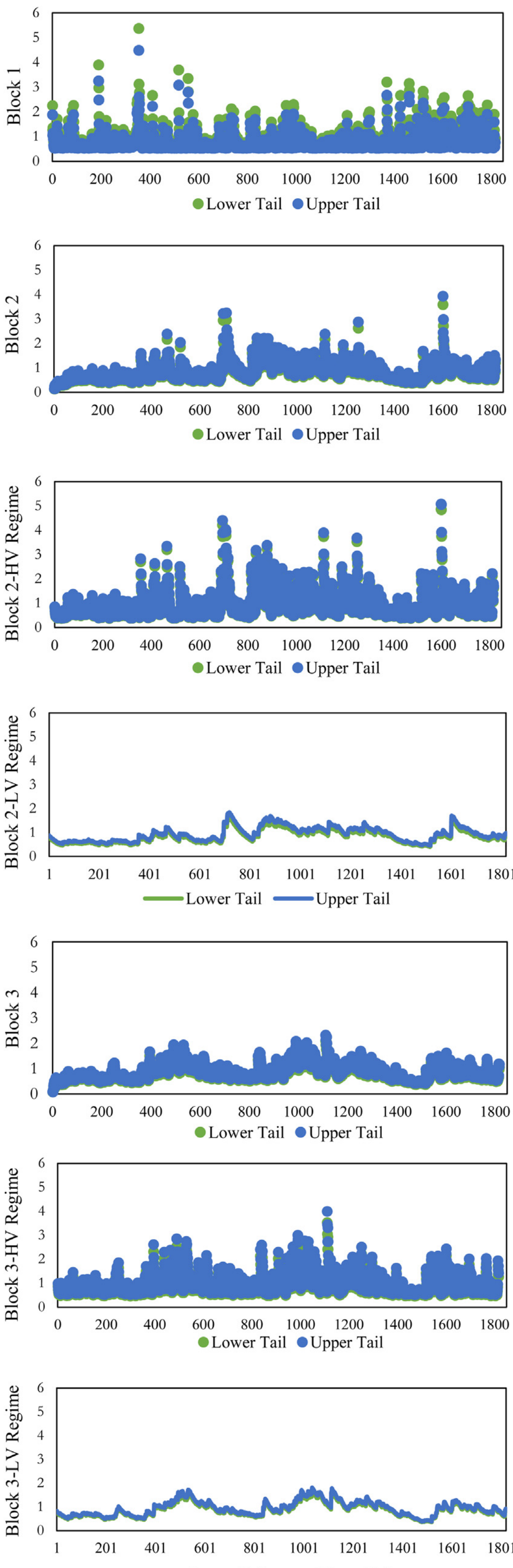

Fig. 6. Value at Risk estimations — 95% confidence level.
The acronyms LV and HV represent the low-volatility regime and high-volatility regime, respectively.

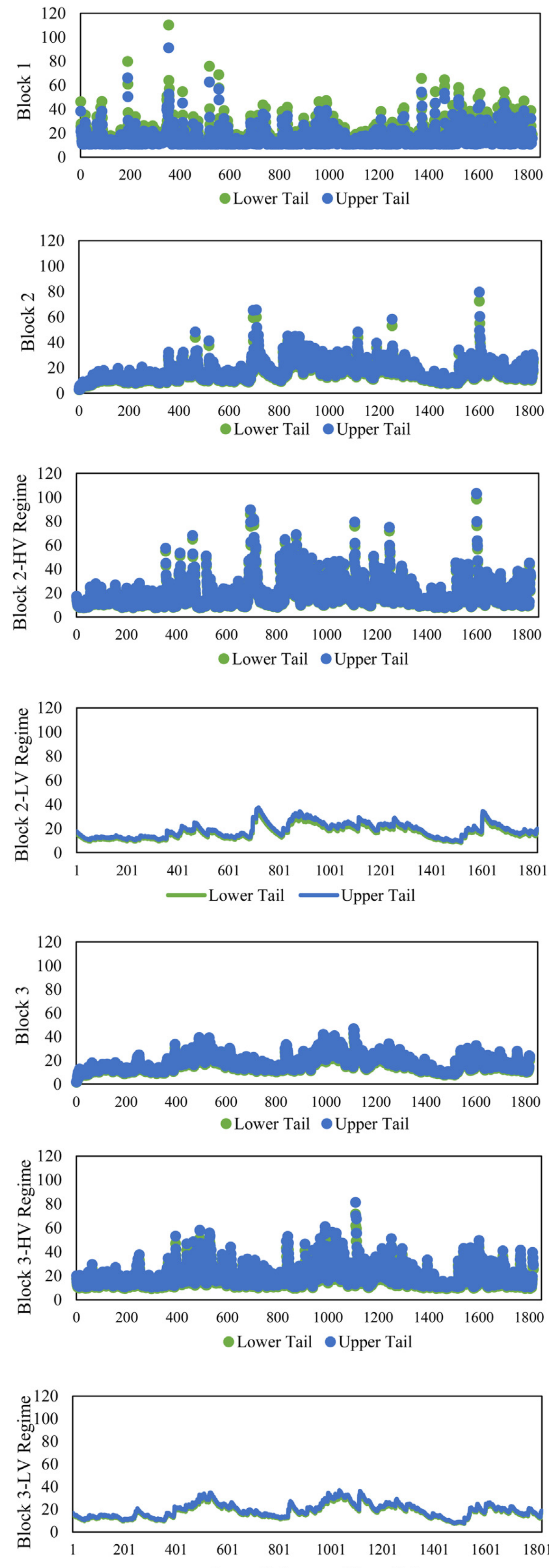

Fig. 7. Conditional Value at Risk estimations — 95% confidence level.
The acronyms LV and HV represent the low-volatility regime and high-volatility regime, respectively.

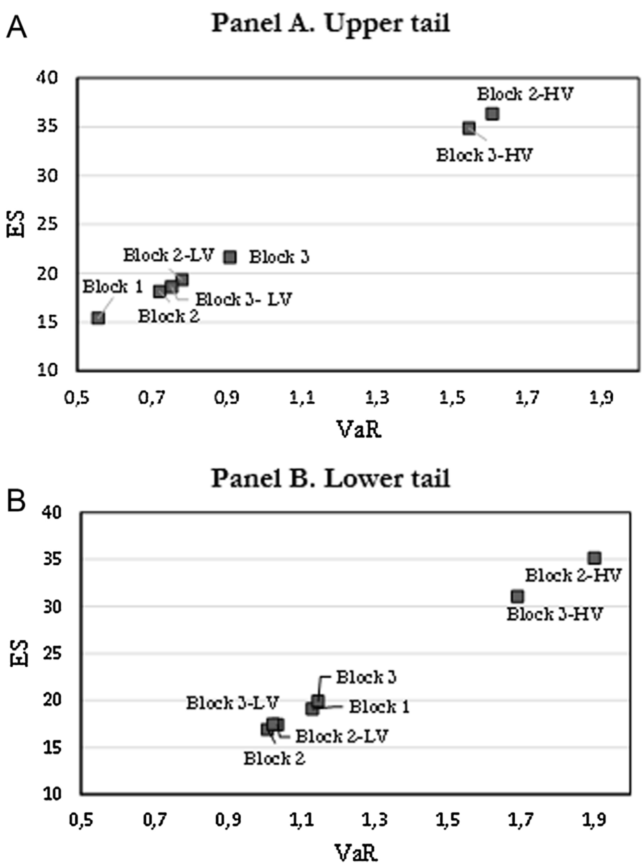

Fig. 8. Example of Value at Risk vs. Conditional Value at Risk — 95% confidence level. The VaR and CVaR estimations correspond to the last variance forecast (the forecast for January 1, 2014). The acronyms LV and HV represent the low-volatility regime and high-volatility regime, respectively.

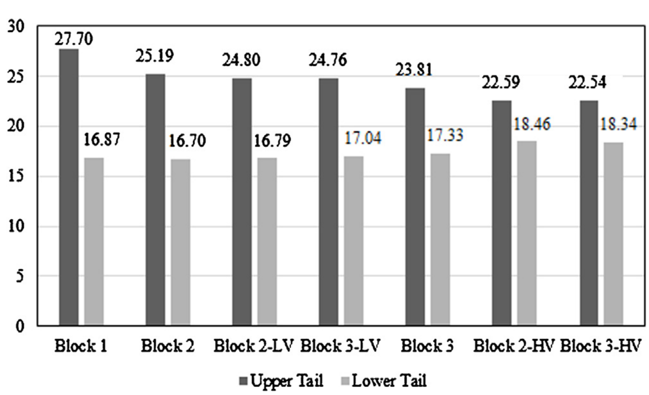

Fig. 9. Example CVaR/VaR — 95% confidence level.
VaR and CVaR estimations correspond to the last variance forecast (the forecast for January 1, 2014). The acronyms LV and HV represent the low-volatility regime and high-volatility regime, respectively.

show VaR statistics for each block and tail of the return distribution, the actual returns and the exceedances (returns that violate the VaR).

performance forecasting risk and fitting the data, compared with the methodology proposed in this paper.

Table 8
Value at Risk duration test.

Upper tail	uLL	rLL	LRp	Decision
Block 1	−431.7260	−432.4011	0.2452	Fail to reject H0
Block 2	−410.8876	−412.8636	0.0468	Fail to reject H0
Block 2 — HV	−407.4507	−410.0361	0.0230	Fail to reject H0
Block 2 — LV	−363.1594	−363.4615	0.4370	Fail to reject H0
Block 3	−411.6727	−412.8636	0.1228	Fail to reject H0
Block 3 — HV	−357.2093	−357.4512	0.4867	Fail to reject H0
Block 3 — LV	−379.7381	−381.2324	0.0838	Fail to reject H0
Lower tail				
	uLL	rLL	LRp	Decision
Block 1	−377.5085	−378.2970	0.2092	Fail to reject H0
Block 2	−404.1869	−404.3531	0.5642	Fail to reject H0
Block 2 — HV	−383.9381	−384.1575	0.5077	Fail to reject H0
Block 2 — LV	−366.3068	−366.4501	0.5924	Fail to reject H0
Block 3	−421.2055	−421.2296	0.8264	Fail to reject H0
Block 3 — HV	−383.9939	−384.1575	0.5673	Fail to reject H0
Block 3 — LV	−332.4646	−332.9499	0.3245	Fail to reject H0

Column uLL reports the unrestricted Log-Likelihood value, rLL the restricted Log-Likelihood value, and LRp the Likelihood Ratio Test Statistic. The test decision on the null hypothesis (H0) is given by the confidence level of 99%. The H0 states that the duration between exceedances have no memory. The acronyms LV and HV represent a low-volatility regime and high-volatility regime, respectively.

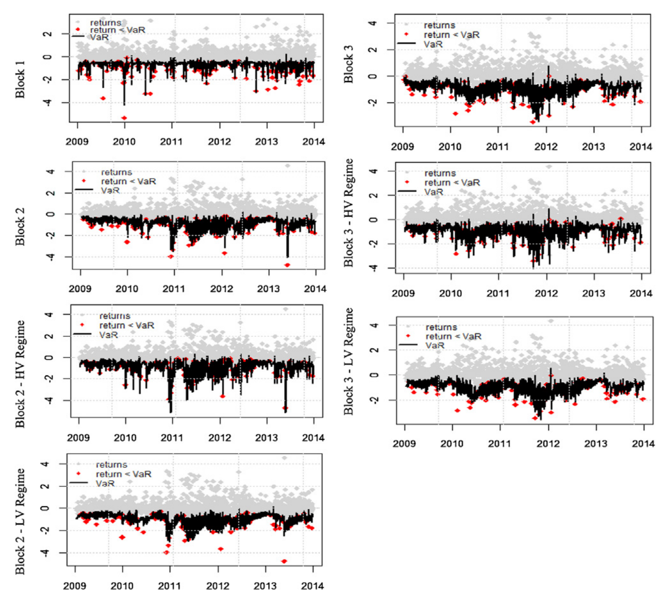

Fig. 10. Returns and Value at Risk exceedances — upper tail.
The acronyms LV and HV represent the low-volatility regime and high-volatility regime, respectively.

4. Conclusions

It has become standard practice to consider conditional heteroskedasticity and heavy-tailed distributions when assessing market risk in electricity markets. Popular methods that are useful for quantifying risk include VaR and CVaR statistics. These methods rely on a proper identification and estimation of the underlying return distribution of electricity prices when making informed decisions about selling and buying strategies, and when deciding between hedging alternatives that are available in the market for electricity consumers and producers.

Nevertheless, those traditional methods lack some desirable properties of particular interest when modeling electricity prices and returns. In the case of electricity markets, accurately modeling the main features presented by price and return distributions

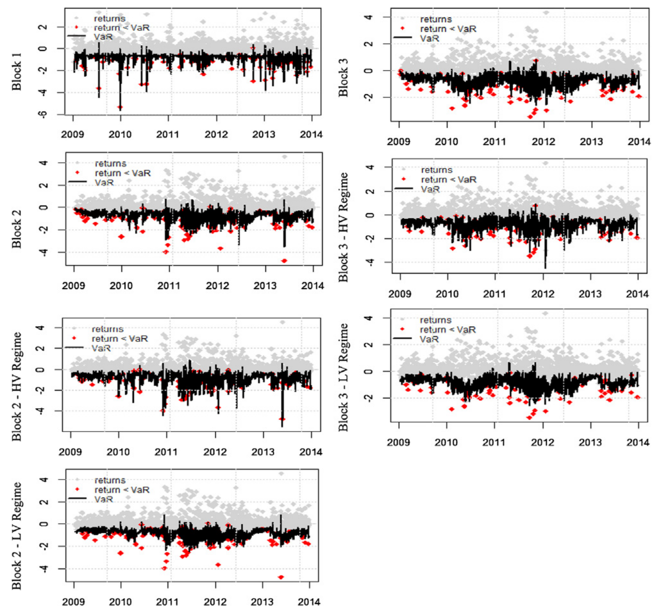

Fig. 11. Returns and Value at Risk exceedances – lower tail.
The acronyms LV and HV represent the low-volatility regime and high-volatility regime, respectively.

has proven to be a challenging task. Prices in these markets are characterized by spikes, strong seasonal patterns (which depend on both the time of the year and the hour of the day when a transaction occurs), long-range memory, volatility clustering, heavy tails, etc. Although traditional models explicitly address some of these phenomena, no model has been developed to take all of them into account. Blending some recent advances in financial econometrics to model electricity prices in a coherent and relatively complete fashion is proposed. This modeling strategy highlights important asymmetries in terms of market variances, block prices, and extreme demand and supply shocks to the market, all of which have the potential to significantly affect risk prospects for users on both sides of the spectrum of electricity markets (consumers and producers).

Features such as changes in unconditional volatility regimes seem to be of first-order importance, particularly in electricity markets, where supply or demand may jump dramatically from one hour to the next, following marked seasonal patterns. Hydrothermal energy markets present significant differences between the costs of power generation associated with the technology used. Hence, the differences in marginal generation cost between hydro and thermal power plants are an important source of variability in electricity prices.

The importance of modeling different hours of the day using different models, perhaps grouping them in terms of price homogeneity, is highlighted. However, it is argued that the trade of an option to be exercised at 20:00 h is not the same as that at 09:00 h in a given day. The risk prospects are markedly different in the two situations. The probability of experiencing extreme events is different, and the expected number of such events differs significantly. Of course, changing weather conditions also play an important role in risk assessments in electricity markets, mainly in terms of the second unconditional moments, as highlighted by the empirical application that was carried out. Clustering and volatility regimes help to improve risk measurement and enrich the information available for electricity firms, traders, and consumers to make educated decisions.

Finally, the tails of the modeled return distribution for electricity prices are compared. Here, the approach followed differs from the common approach in the literature, which mainly ignores possible asymmetries in the tails and focuses on only one tail (generally the positive tail). Thus, it is found that important and statistically significant asymmetries do exist in the risk faced by electricity consumers and producers. These asymmetries are not conclusive in the sense that one could ensure that the risk is always greater on one side of the spectrum or the other. Instead, risk asymmetries are important and significant, but changing. Sometimes, the risk faced by producers is higher than the risk faced by consumers; other times, the opposite holds true.

Interestingly, a complex interplay between conditional skewness and conditional kurtosis of the returns distribution is documented, when the tails of the distribution of electricity returns are characterized by means of extreme statistics, such as VaR and CVaR. That is, in some blocks of the day, the VaR and CVaR are higher at the right tail because a given confidence threshold is higher than the analogous threshold at the left tail (i.e., there is asymmetry in the distribution). However, in other cases, the risk is higher in the opposite tail, not because of the skewness, but because the probability of experiencing an extreme event, related to "tail" parameters, is also generally different for consumers and producers. A paired VaR and CVaR estimation seems to be able to properly address these types of asymmetries, provided the analyst does not assume symmetric tails to start with.

By highlighting the asymmetries of risk in electricity markets, this paper aims to address the importance of considering complete models when measuring risk and pricing derivatives in electricity markets. These asymmetries are crucial for the correct design of hedging strategies according to the agent's role in the market (consumer, producer, distributer or investor). This model is unlikely to be the final one, and further extensions and comparisons (if forecasting is of interest) will be required, but it could serve as a new starting point for pricing and quantifying complex risks associated with electricity commodities, particularly for those depending on hydrothermal-based generation systems. Moreover, the proposed methodology can be explored with other renewable energy sources, since all energy markets exhibit prices with high volatilities and marked spikes that likely would present different volatility regimes and asymmetric tail-distribution dynamics.

Appendix A. Value at Risk duration test – alternative methods of estimation.

Upper tail				
	uLL	rLL	LRp	Decision
ARMA-GARCH normal	−354.2571	−357.5491	0.0103	Reject H0
Historical	−411.4773	−412.9824	0.0827	Fail to reject H0
ARMA-GARCH Montecarlo	−329.8996	−333.0390	0.0122	Reject H0
Lower tail				
	uLL	rLL	LRp	Decision
ARMA-GARCH normal	−313.3442	−317.3235	0.0048	Reject H0
Historical	−306.5921	−310.9463	0.0032	Reject H0
ARMA-GARCH Montecarlo	−325.4815	−329.9212	0.0029	Reject H0

Column uLL reports the unrestricted Log-Likelihood value, rLL the restricted Log-Likelihood value, and LRp the Likelihood Ratio Test Statistic. The test decision on the null hypothesis (H0) is given by the confidence level of 95%. The H0 states that the duration between exceedances have no memory.

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