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Research Paper

The Iberian electricity market: analysis of the risk premium in an illiquid market

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ABSTRACT

This paper analyzes the risk premium in the base-load monthly futures contracts traded on the Iberian electricity market (MIBEL) between July 1, 2006 and March 31, 2017. During this time span, the ex post risk premium on the last trading day presented a relative mean value of -5.77% as well as negative skewness, excess kurtosis and some persistence. The risk premium depended on the season of the year, with the absolute value for winter futures being more than five times higher than for summer futures. The absolute risk premium and its volatility decreased nonlinearly throughout the remaining trading days until maturity. There is no statistical evidence for rejecting an unbiased forward hypothesis; however, the sequence of futures prices approaching maturity showed some predictive power as regards the risk premium. The futures price path between seven and three days prior to delivery explained around 28% of the variability in the risk premium, and there is some evidence that this information can be used to successfully forecast the risk premium signal.

Keywords: Iberian electricity market (MIBEL); Operador do Mercado Ibérico de Energia (OMIP); electricity futures contract; risk premium.

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1 INTRODUCTION

Electricity is not storable in economically meaningful quantities. Sudden variations in electricity supply or demand cannot be accommodated via inventory management, hence the need for a permanent equilibrium between both sides of the market. For these reasons, maintaining the efficiency of electricity markets is a challenging task, requiring additional balancing services and reserve resources management beyond the common production and distribution services.

Recently, electricity markets have experienced a worldwide deregulation trend, which has led to the creation of new electricity spot and derivatives exchanges, where, for instance, futures and forward contracts are traded. These contracts are agreements for deferred transactions, in which the seller agrees to deliver to the buyer, at an agreed price, a specific quantity of electricity at a fixed time in the future. Although fundamentally similar, forward contracts are informal bilateral agreements traded over the counter, while futures are standardized contracts traded on exchange. Therefore, futures tend to provide a liquid, low-cost way to manage price uncertainty or to speculate on the future price of electricity. By entering into a futures contract, traders resolve the uncertainty of future electricity prices, while guaranteeing a future market for their purchases for consumption or sales of their product. The rationale behind electricity futures markets is to provide not only risk management through hedging but also price discovery. Hedgers use futures to shift price risk to other market participants, usually speculators, who accept it in the hope that they may profit from their expectations. However, futures markets, by providing a multilateral centralized venue, also enable fundamental information about electricity supply and demand gathered by traders to pass efficiently to the price system, therefore uncovering the future spot equilibrium price. Ultimately, more accurate prices improve intertemporal allocative efficiency. The performance of the futures market as a provider of these two economic benefits (ie, risk management through hedging and price discovery) depends on the correlation between the futures price and the contemporaneous electricity spot price, and on the difference between the spot price at delivery and the current futures price, that is, the amplitude of the risk premium.[1]

Several theoretical models have been proposed to describe and explain the risk premium in electricity futures. The best known of these is the equilibrium model of Bessembinder and Lemmon (2002), which suggests that the forward risk premium depends on the market forecasts for the variance and asymmetry of electricity spot price at delivery. Other models can be found in the literature. For example, Cartea and Figueroa (2005) propose a mean-reverting jump diffusion process for the electricity

[1] In the interest of clarity, we follow Weron and Zator (2014) throughout this paper and define the "risk premium" as the spot price at delivery minus the current futures price, while the forward risk premium is the negative of the risk premium.

spot price, while Cartea and Villaplana (2008), assuming that wholesale electricity prices are driven by demand and capacity, derive analytical expressions for the risk premium. Along the same line of reasoning, Pirrong and Jermakyan (2008) use a two-state price model based on demand (load) and fuel price to study the risk premium.

Though much of the literature uses different procedures, based on the study of different markets, the empirical evidence for the existence of a risk premium in electricity futures markets is, by now, quite compelling. Shawky *et al* (2003) show the existence of a risk premium in the futures traded on the New York Mercantile Exchange. The risk premium for the German electricity market is analyzed by Benth *et al* (2008), who demonstrate the existence of a term structure in the risk premium, originating from the interactions between risk-averse market participants. Pietz (2009) provides evidence for the existence of a positive forward risk premium in the electricity futures for delivery in Germany traded on the European Energy Exchange (EEX). Redl *et al* (2009) find the spot price skewness to be significant in determining the base-load futures spot bias, whereas the spot price variance positively influences the risk premium in peak-load contracts in the EEX market. Lucia and Torró (2011) study the forward risk premium in the Nord Pool electricity market, finding that it presents a positive value on average but also displays a dynamic nature. This market is also studied by Botterud *et al* (2010), who find a relationship between the risk premium and information about reservoir, inflow and electricity consumption. This work is revisited by Weron and Zator (2014), who evidence the positive impact of water reservoir seasonal levels on the risk premium. Haugom *et al* (2014) study the weekly futures traded on the Nordic power market, where they find a positive risk premium that varies across the seasons and tends to diminish over time; they do not, however, reject the unbiased forward hypothesis. These results are in line with those of Haugom and Ullrich (2012) for the day-ahead futures traded on the Pennsylvania–New Jersey–Maryland (PJM) market. Umutlu *et al* (2011) show that futures prices traded on the Amsterdam Power Exchange are not unbiased predictors of future spot prices. The effect of fundamental, behavioral, dynamic and shock components on electricity is analyzed by Redl and Bunn (2013) within the EEX forward market. Following the same line of reasoning, a value-at-risk (VaR) model is used by Bunn and Chen (2013) to distinguish between fundamental and behavioral determinants of prices and risk premiums in the British market. Using empirical enlargement filtration techniques, Benth *et al* (2013) find that a significant part of the risk premium in electricity forward contracts may be attributed to different information sets in the spot and forward markets. The risk premium on monthly, quarterly and annual electricity forward contracts traded on the Nordic and German/Austrian markets is examined by Fleten *et al* (2015) using daily futures returns. They find a positive average risk premium when producers hedge their production; however, this has a tendency to become negative (on average) when large buyers enter into the market.

There is also some empirical evidence on the Iberian electricity market (MIBEL). Cartea and Villaplana (2014) show the existence of a linear dependence between ex post risk premiums in the electricity markets of Germany, France and Spain. The existence of unidirectional causality from the futures to the forward and spot markets is confirmed by Ballester *et al* (2016), suggesting that futures prices are used by market participants as reference prices. Herráiz and Monroy (2009) demonstrate the presence of a risk premium and reject the market efficiency hypothesis for the Iberian futures market as well as other European power markets. Furió and Meneu (2010) argue that the sign and magnitude of the risk premium depend on unexpected variations in both demand and hydroelectric capacity. The forward risk premium is shown to be negatively related to the spot price variance.

This paper contributes to the existing literature by examining, using an up-to-date sample, the dynamics and predictability of the risk premium in a peripheral and illiquid electricity market: MIBEL. Most papers on MIBEL focus solely on the spot market; alternatively, they might incorporate supply-and-demand fundamentals into their analyses (see, for instance, Lagarto *et al* 2012; Miranian *et al* 2013; Monteiro *et al* 2015). Our perspective is somewhat different in that we focus only on the financial dimension of this market. We present some statistical properties of the spot and futures prices and the risk premium. Using simple modeling tools, we also give valuable insights into risk premium predictability, showing that the use of futures prices near delivery has some predictive power.

This paper is organized as follows. Section 2 gives a brief introduction to the basic structure of MIBEL and describes the data set. Results on the spot and futures price dynamics are presented in Section 3. Section 4 presents the dynamics of the risk premium, tests the unbiased forward hypothesis and gives some insight into its predictability. Section 5 concludes the paper.

2 THE IBERIAN ELECTRICITY MARKET

MIBEL is a joint wholesale electricity market comprising Spain and Portugal. This market allows for interaction between several types of buyer, such as reference retailers, resellers, direct consumers and sellers (ie, electricity power producers). The spot market is managed and regulated by the Spanish division of the Iberian Energy Market Operator (OMIE). The spot market is composed of the daily market and the intraday market. The daily market sets electricity prices for the twenty-four hours of the following day (the day-ahead market). Prices and volumes are determined via the equilibrium between supply and demand for each hour of the following day, and therefore within a marginal pricing framework. When the traded electricity exceeds the interconnection network capacity between Spain and Portugal, a market splitting mechanism commences and different electricity prices are set for each country. The technical viability of the daily market schedule is guaranteed by the system operator. Adjustments to the final viable daily schedule are conducted via the intraday markets. Once the daily market closes, six intraday market sessions are held, in which market participants may adjust their positions up to four hours ahead of real-time delivery.

The Operador do Mercado Ibérico de Energia (OMIP) is responsible for organizing and managing the derivatives section of MIBEL. The electricity derivatives available for trading in OMIP are futures, options, swaps and forward contracts. There are base-load and peak-load derivative products. The delivery period for base-load derivatives covers all daily hours, while peak-load derivatives cover peak hours only (typically from 08:00 to 19:00). The underlying asset of all futures contracts is a supply of electric energy at a constant power of 1 megawatt hour (MWh) during each hour of the delivery period. These contracts are quoted in euros per MWh (€/MWh) and the available delivery periods are day, weekend, week, month, quarter and year. The delivery price is computed using a spot price reference index. Day and weekend futures are subjected to financial delivery, while the other kinds of futures are suitable for financial or physical delivery. For these futures, market participants choose the type of delivery when opening their positions.

The Iberian Energy Clearing House (OMIClear) performs the role of clearing house, central counterparty and settlement system. Bilateral transactions can also be registered through OMIClear. Two trading systems coexist within OMIP: the continuous market and the call auction market (Herráiz and Monroy 2009). Continuous trading is the default trading mode, via which anonymous buy and sell orders are matched immediately, according to the best pricing rule, generating an undetermined number of trades and prices in each trading session. With the second trading mode, a single-price auction maximizes the trading volume, with all trades being settled at the same price.

This study uses daily spot and futures prices extracted from the OMIP web page. The data covers the period between July 1, 2006 and March 31, 2017. Both spot and futures prices correspond with the Spanish zone of MIBEL. The spot reference price, which is also the price considered by OMIClear for computing the delivery price, is the daily Spanish electricity (SPEL) base index, computed as the arithmetic mean of hourly marginal prices for the hours covered by the delivery schedule.

The futures prices are given by the settlement prices, fixed by OMIP on a daily basis for the purpose of marking-to-market, until the last trading day. We only consider the SPEL base-load futures contracts with monthly (physical and financial) delivery. For these contracts, the last trading day coincides with the last business day before the delivery month. A total of 128 monthly contracts were traded during the sample period. The reason we have chosen to work with monthly SPEL base-load futures has to do with liquidity concerns only. The Iberian electricity futures market is highly illiquid, with just a few contracts being traded each day. The distribution of volume

FIGURE 1 Average number of trades on monthly base-load futures contracts.

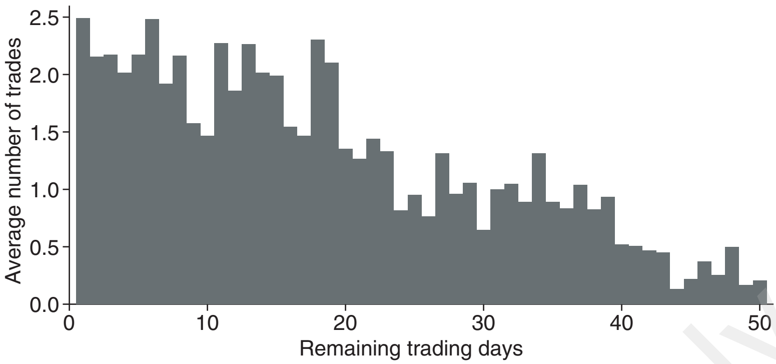
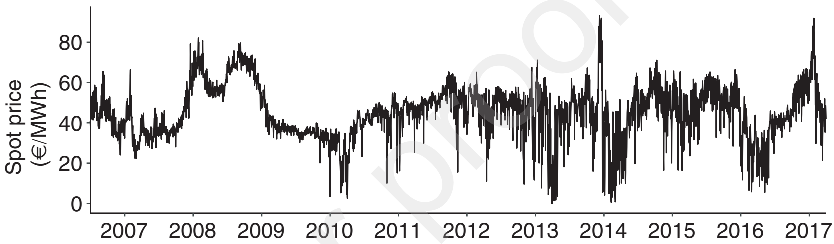


FIGURE 2 Daily day-ahead spot prices (€/MWh) from July 1, 2006 until March 31, 2017.



across mid- and long-term base-load futures contracts is as follows: monthly, 50%; quarterly, 37%; and yearly, 13%.

Figure 1 presents the distribution of the number of trades made on monthly base-load futures per trading day until delivery. As expected, the average number of trades increases gradually as contracts approach the delivery month; liquidity, however, is quite low, achieving an averaged maximum of only 2.5 trades per day.

3 SPOT AND FUTURES PRICE DYNAMICS

Figure 2 shows the daily SPEL (that is, the twenty-four-hour arithmetic mean) path for the overall sample.

The daily spot prices display frequent extreme values and high volatility clustering. The positive extreme values correspond with periods of unanticipated high demand for electricity, while the negative extreme values result from a low-cost electricity generation mix combined with system saturation. The high volatility clustering results from an inability to smooth the supply-and-demand interrelationship via inventories (Higgs and Worthington 2008). The spot prices seem to follow a mean-reversion process, that is, they fluctuate around a long-term equilibrium value. All these features are typical of electricity markets and are often attributed to the nonstorable nature of electricity as well as the reduced number of market players.

A statistical summary of spot prices can be found in Table 1. The sample mean is 45.33 €/MWh and the standard deviation is 13.51 €/MWh. The highest spot price is 93.11 €/MWh (December 8, 2013), while electricity was provided free of charge on April 1, 2013 and March 29, 2014. The negative skewness indicates more frequent downward spikes, while there is mild excess kurtosis. The augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests reject the null hypothesis of a unit root, and thus the spot prices seem stationary.

Weather conditions tend to produce monthly and season of the year seasonalities, while economic and business activities generate seasonalities on several time scales: intraday, daily, weekly and monthly. For instance, business electricity demand is higher during business hours than at night and lower on weekends than on business days. The electricity supply tends also to present seasonalities. For instance, it is dependent on water reservoir levels, which, in turn, depend mostly on weather conditions. Because we will be dealing with monthly futures, we consider only monthly and season of the year seasonalities. Figure 3 shows the average price and volatility by month, while Table 1 presents some descriptive statistics by season of the year.[2]

The lowest and highest average spot prices are observed in April and September, respectively. Lower volatility values occur in May and June, while higher values occur in January and February. This seasonal feature is also shown in Table 1, where we observe a low average price in the spring and higher volatility in the winter.

Yearly spot price statistics are presented in Table 1. The mean ranges from 35.32 €/MWh in 2016 to 64.43 €/MWh in 2008, while the standard deviation ranges from 5.58 €/MWh in 2009 to 17.46 €/MWh in 2013. Most of these years present negative skewness and excess kurtosis, but there is no discernible pattern.

Table 1 highlights some particular events that happened during the period under scrutiny. First, the financial crisis of 2009 affected several energy commodity prices (gas, oil and coal) along with wholesale and retail electricity prices worldwide. This

[2] Monthly and season of the year volatilities are computed using the square root of the second central moment of the daily SPEL index (the arithmetic mean of hourly marginal spot prices for all twenty-four hours of the day) for each period. For instance, the March volatility is computed using all the daily observations in that month across the overall sample.

TABLE 1 Descriptive statistics on daily spot prices.

(a) Overall sample

	Spot prices
Maximum	93.11*
Minimum	0.00**
Mean	45.33
SD	13.51
Skewness	−0.25
Kurtosis	3.83
ADF	−5.83
PP	−433.92

(b) Season of the year

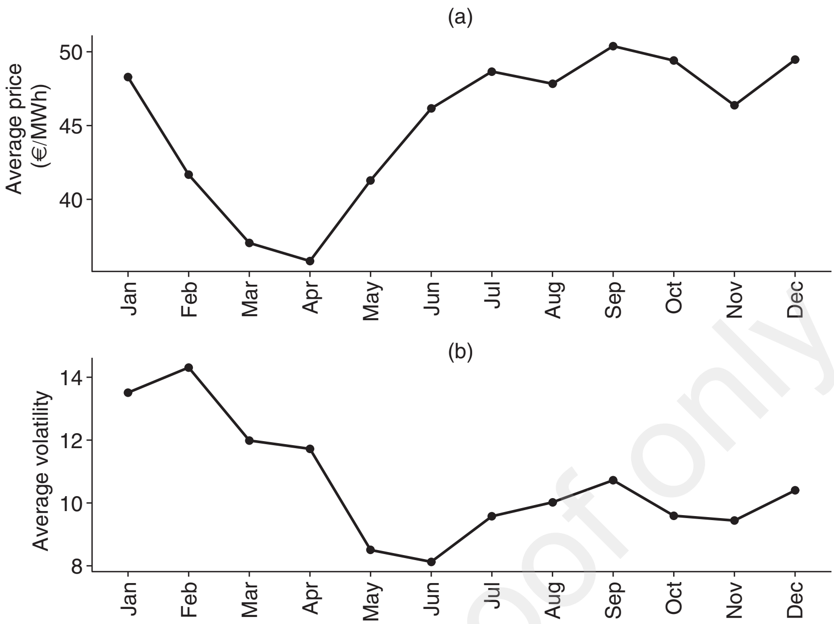
	Fall	Spring	Summer	Winter
Maximum	79.65	66.73	75.86	93.11
Minimum	9.55	0.00	18.18	0.48
Mean	48.73	38.04	47.61	46.64
SD	11.41	13.22	9.98	15.99
Skewness	0.17	−0.65	0.38	−0.16
Kurtosis	2.88	3.25	2.76	3.32

(c) Yearly subsamples

	2006	2007	2008	2009	2010	2011
Mean	44.28	39.35	64.43	36.96	37.01	49.92
SD	8.33	8.86	7.19	5.58	10.63	6.92
Skewness	0.19	1.24	−0.07	0.46	−1.07	−1.16
Kurtosis	0.19	4.92	2.20	9.00	3.79	7.48
	2012	**2013**	**2014**	**2015**	**2016**	**2017**
Mean	47.24	44.26	42.13	50.32	35.32	55.60
SD	8.84	17.46	15.66	9.26	10.91	14.62
Skewness	−1.36	−0.43	−0.86	−0.84	−0.54	0.47
Kurtosis	5.55	4.06	3.11	3.84	3.10	2.87

This table shows some descriptive statistics on the daily spot prices for the overall sample, given the season of the year and on a yearly basis. The sample comprises the period from July 1, 2006 until March 31, 2017, hence the first and last years are incomplete. The augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests examine the null hypothesis for the presence of a unit root. All these statistics are significant at the 1% level. An asterisk (*) indicates the maximum spot price, obtained on December 8, 2013; two asterisks (**) indicate the minimum spot price, obtained on April 1, 2013 and March 29, 2014. SD denotes standard deviation.

FIGURE 3 (a) Monthly averages of daily spot prices and (b) volatility values.



also happened in MIBEL, where the average price decreased from 64.43 €/MWh in 2008 to 36.962 €/MWh in 2009. In this year, the electricity price reached a minimum value of 3.40 €/MWh and remained low in 2010. Due to low demand and the abundance of renewable energy, the MIBEL prices went down to 0 €/MWh for several hours during February and March of 2010 (European Commission 2010). Second, the spot price variation in 2013 is noteworthy, ranging from 0 €/MWh on April 1, 2013 to 93.11 €/MWh on December 8, 2013 (the highest value recorded in the sample). In April 2013, a generation mix, mainly composed of low-cost hydropower and other renewable energies, led to several days with prices between 0 €/MWh and 10 €/MWh (European Commission 2013). However, in December 2013 the wind and hydro-based power generation declined substantially, resulting in a generation mix mainly composed of expensive conventional sources; this, in turn, drove the price up to 93.11 €/MWh (European Commission 2014).

In order to analyze the futures price dynamics, we define three time series, corresponding with one month-, two months- and three months-ahead monthly contracts (the statistics for which are shown in Table 2). The spot price is more volatile than the futures market, while the futures volatility increases as contracts approach the delivery

TABLE 2 Descriptive statistics on the one month-, two months- and three months-ahead monthly futures prices.

	One month ahead	Two months ahead	Three months ahead
Maximum	74.50	76.13	75.38
Minimum	24.25	26.88	28.75
Mean	48.13	48.90	49.04
SD	9.25	8.70	7.92
Skewness	0.23	0.35	0.58
Kurtosis	3.16	3.31	3.56
ADF	–3.57	–3.60	–3.26
	(0.04)	(0.03)	(0.08)
PP	–24.78	–24.03	–22.70
	(0.03)	(0.03)	(0.04)

"ADF" and "PP" refer to the augmented Dickey–Fuller and Phillips–Perron tests on the null hypothesis of the presence of a unit root, respectively. The p-values of these statistics are in parentheses.

month. This last tendency is in accordance with the so-called Samuelson effect (for a study on this issue and its application to electricity futures, see Jaeck and Lautier (2016)). The price skewness and kurtosis of the futures decrease when approaching delivery, showing that the futures price distribution becomes less asymmetrical and leptokurtic. Possible explanations for these results are that, as the delivery month approaches, market participants become better placed to forecast future positive shifts in the spot price, while at the same time the price impact of their trades decreases due to the higher liquidity of the futures market.

4 THE RISK PREMIUM

There are two main pricing theories for the futures contracts on commodities: the cost-of-carry model and the hedging pressure theory. The former theory states that, at equilibrium, which is characterized by the no-arbitrage condition,

$$F_{t,T} = S_t e^{(r+q-c)T}, \tag{4.1}$$

where $F_{t,T}$ is the futures price at time t with holding period T and delivery starting at $t + T$, S_t is the spot price of the underlying commodity at time t, r is the time-independent risk-free rate, and q and c are the continuous rate of storage costs and the continuous convenience yield, respectively. The model assumes the feasibility of carrying forward the underlying commodity, hence it only holds perfectly for storable commodities.

The hedging pressure theory is valid for both storable and nonstorable commodities, and therefore it is more appropriate for pricing electricity futures. The theory is built on the idea that futures contracts are hedging instruments, as they protect investors against unexpected future price changes of the underlying asset. Hence, futures prices reflect the expected price of the underlying asset at delivery, plus a risk premium, which constitutes the implicit cost associated with transferring the risk between market agents. Its sign depends on whether the hedging pressure is mainly on the buy or sell side of the market. Sellers with a more risk-averse posture than buyers are willing to accept a lower futures price; if the risk aversion is mainly on the demand side, buyers will accommodate a higher futures price.

The risk premium may be defined as ex ante,

$$\mathrm{RP}_{t,T}^{\text{ex ante}} = \ln(\mathrm{E}_t[S_{t+T}]) - \ln(F_{t,T}), \tag{4.2}$$

or ex post,

$$\mathrm{RP}_{t,T}^{\text{ex post}} = \ln(\bar{S}_{t+T}) - \ln(F_{t,T}), \tag{4.3}$$

where $\mathrm{E}_t[\cdot]$ represents the conditional expectation at time t, and $\bar{S}_{t+T}$ denotes the realized spot price over the delivery period starting at $t+T$. Because the expected price is not observable, the ex ante computation of the risk premium requires modeling the dynamics of the underlying asset, which, depending on the model used, may result in distinct estimates. The ex ante risk premium can be written as the ex post risk premium, plus a forecast error:

$$\mathrm{RP}_{t,T}^{\text{ex ante}} = \mathrm{RP}_{t,T}^{\text{ex post}} + \{\ln(\mathrm{E}_t[S_{t+T}]) - \ln(\bar{S}_{t+T})\}. \tag{4.4}$$

The forecast error is the difference between the expected spot price and the realized spot price at delivery, and it is generally assumed to be white noise. Thus, the ex post risk premium is a good proxy for the ex ante risk premium, and evidence of a nonzero ex post risk premium also constitutes evidence of a nonzero ex ante risk premium. Herein, we analyze the ex post risk premium of the SPEL base-load futures contracts for monthly delivery, which is hereafter referred to as simply "risk premium" and computed according to

$$\mathrm{RP}_{t,1} = \ln(\bar{S}_{t+1}) - \ln(F_{t,1}). \tag{4.5}$$

More precisely, we use the average of the realized spot price over the corresponding futures delivery month and the futures settlement price on the last trading day (for notation purposes, we assume that on the last trading day the futures' holding period is $T = 1$).

FIGURE 4 The risk premium time series (all values shown are percentages).

4.1 Risk premium dynamics

The time series of the monthly risk premiums (as percentages) is displayed in Figure 4, and its descriptive statistics are presented in Table 3.

The minimum and maximum risk premiums occurred in April 2013 and December 2013, respectively, as a result of the particular events described in Section 3, implying that the futures market did not anticipate these events. The risk premium is negative for much of the time (66.41%) with mean and median values of −5.77% and −4.17%, respectively. This negative risk premium indicates that market agents are willing to pay higher futures prices in order to reduce their risk exposure to electricity price increases. The risk premium is quite volatile and its skewness and kurtosis indicate that there are frequent jumps, especially negative ones (see Figure 4). The first-order autocorrelation is 0.28, which denotes some persistence. According to the ADF and PP tests, the risk premium series is stationary.

The statistics on the risk premium by season of the year are reported in Table 4. On average, the winter futures were traded 12.4% higher than the realized spot prices, while the summer futures were traded just 2.1% above their respective realized spot prices. The risk premium volatility was at its highest in the winter and its lowest in the summer. Hence, the lowest risk premium level and volatility reflect a higher predictability during the summer months.

An issue usually addressed in studies of this kind is the term structure of the risk premium. We compute the average risk premium and its volatility over all contracts as a function of the trading days until delivery; that is, the average risk premium for a particular day – taking into consideration the number of days until delivery – is averaged over all contracts. We also present the term structure of the correlation between the futures and the spot prices and the futures price volatility as functions of the trading days until delivery (see Figure 5).

The risk premium level and volatility depend nonlinearly on the number of trading days until delivery, which can be closely modeled by a square root process on T, with

TABLE 3 Descriptive statistics on the risk premium (%).

	Risk premium
No. obs	128
% negative	66.41
Maximum	22.93
Contract	December 2013
Minimum	−71.68
Contract	April 2013
Median	−4.17
Mean	−5.77
SD	14.18
Skewness	−2.02
Kurtosis	9.72
$\rho(1)$	0.28
ADF	−4.29
PP	−140.63

First-order autocorrelation is denoted by $\rho(1)$. "ADF" and "PP" refer to the augmented Dickey–Fuller and Phillips–Perron tests on the null hypothesis of the presence of a unit root, respectively. These statistics are significant at the 1% level.

TABLE 4 Descriptive statistics on the risk premium (%) per season of the year.

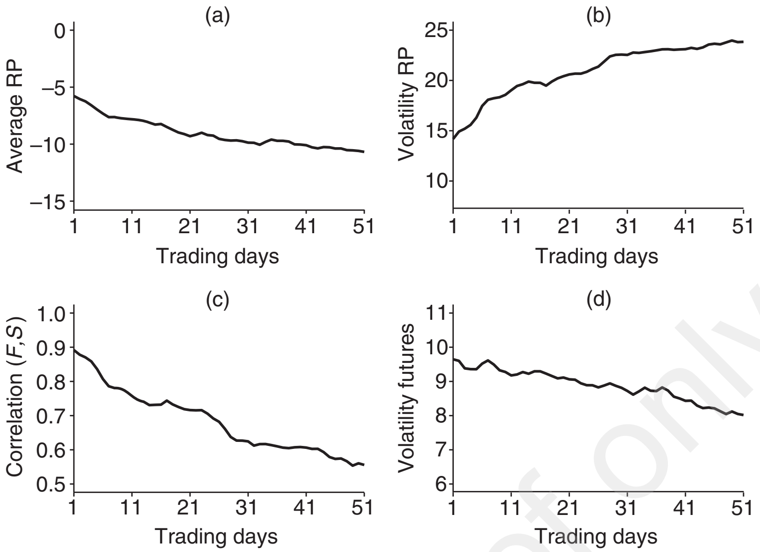
	Fall	Spring	Summer	Winter
Maximum	22.93	16.27	16.47	19.20
Minimum	−30.37	−71.68	−16.92	−70.67
Mean	−2.56	−5.98	−2.06	−12.40
SD	10.43	15.33	6.95	18.97
Skewness	−0.11	−2.67	0.30	−1.23
Kurtosis	3.65	12.49	3.24	4.46

$T = 1$ representing the last trading day.[3] The correlation between the realized spot average and the futures prices can be modeled in the same way. The ordinary least squares (OLS) estimates, all significant at the 1% level, are as follows:

$$\begin{aligned}
\text{Average } \mathrm{RP}_{t,T} &= -5.31 - 0.77\sqrt{T}, \quad R^2 = 0.97,\\
\text{Volatility } \mathrm{RP}_{t,T} &= 13.41 + 1.56\sqrt{T}, \quad R^2 = 0.97,\\
\mathrm{Corr}(\bar{S}_{t+T}, F_{t,T}) &= 0.95 - 0.06\sqrt{T}, \quad R^2 = 0.98.
\end{aligned}$$

[3] Following Pietz (2009), we also regressed the risk premium level on the number and squared number of trading days until delivery, with slightly lower coefficients of determination.

FIGURE 5 The term structure of the risk premium.



Parts (a) and (b) show the term structure of the level and the volatility of the risk premium (%), respectively. Parts (c) and (d) show the correlation between the realized spot price and the futures price, and the futures price volatility, respectively. The x axis shows the remaining number of trading days until delivery.

The futures price volatility displays a linear dependence on the remaining trading days,

$$\text{Volatility } F_{t,T} = 9.66 - 0.02T, \quad R^2 = 0.95,$$

where the estimated values are also significant at the 1% level.

As expected, the risk premium decreases, in absolute value, as the futures contracts approach the last trading day. For instance, the risk premium computed as $\ln(\bar{S}_{t+T}) - \ln(\bar{F}_{t,[1,30]})$, where $\bar{F}_{t,[1,30]}$ is the average of the futures settlement prices over the last thirty trading days before delivery, has a mean of -7.78% and a volatility of 18.01. The futures volatility increases as delivery approaches (providing further evidence for the existence of the Samuelson effect), but this is also true of the correlation between the futures and spot prices, and at an even higher rate. These two effects combined result in a decrease in the risk premium volatility as the delivery month approaches.

These results imply that, as delivery approaches, the importance of the fundamental determinants behind the difference between the current futures price and the future spot price decreases. However, this also suggests that, as time passes, market players have more information on spot prices for the subsequent month, leading them to revise their expectations accordingly. Arguably, trading on information tends to improve the

TABLE 5 Tests on the unbiased forward hypothesis.

	$F_{t,1}$			$\bar{F}_{t,[1,10]}$
	OLS	**OLS (−3 lowest obs)**	**Robust**	**Robust**
α	−4.80 (0.018)	−2.74 (0.14)	−2.46 (0.21)	−2.08 (0.42)
β	1.06 (0.00)	1.02 (0.00)	1.02 (0.00)	1.00 (0.00)
H_0: $\beta = 1$	(0.14)	(0.55)	(0.69)	(0.97)
R^2	0.80	0.82	0.87	0.79
$Q(10)$	11.47 (0.32)	8.34 (0.60)	13.07 (0.22)	14.84 (0.14)
$Q^2(10)$	50.18 (0.00)	12.05 (0.28)	50.31 (0.00)	61.88 (0.00)

$F_{t,1}$ and $\bar{F}_{t,[1,10]}$ designate the futures price at the last trading day and as the averaged price in the last ten trading days, respectively. Equation (4.6) was estimated for $F_{t,1}$ by using OLS on all the data and on the data without the three lowest extreme values, ie, OLS (−3 lowest obs) as well as by the Tukey's biweight robust estimator. This estimator was also used for $\bar{F}_{t,[1,10]}$. The p-values, presented in parentheses, use the Newey–West autocorrelation–heteroscedasticity robust standard errors, with a bandwidth equal to three (the Bartlett kernel). The line H_0: $\beta = 1$ presents the p-values on the null hypothesis of no bias in the forecast. The table also presents Ljung–Box statistics on the null hypothesis of no autocorrelation in residuals, $Q(10)$, and squared residuals, $Q^2(10)$, for ten lags.

properties of the futures price as a predictor of the future spot price as delivery approaches.

4.2 Unbiased forward hypothesis and risk premium predictability

A simple way to test the unbiased forward hypothesis is via the following equation (Haugom and Ullrich 2012):

$$\bar{S}_{t+T} = \alpha + \beta F_{t,T} + \epsilon_{t+T}. \tag{4.6}$$

The futures prices provide unbiased forecasts of future spot prices if $\alpha = 0$ and $\beta = 1$. In other words, any α value that is significantly different from 0 indicates the presence of a systematic risk premium, and any β significantly different from 1 shows evidence of a biased prediction and, thus, a forecast error. The linear regression given by (4.6) is estimated using the futures price on the last trading day, $F_{t,1}$ as well as the averaged price for the last ten trading days, $\bar{F}_{t,[1,10]}$. Table 5 presents the results.

Although the mainstream literature provides empirical evidence against this hypothesis in the electricity futures markets, we are not able to reject this hypothesis for the Iberian market. This is in line with the results presented by Haugom and Ullrich (2012) for the PJM market and Haugom *et al* (2014) for the Nord Pool power market. Using OLS, the intercept for the $F_{t,1}$ regression is statistically different from zero at the

5% level; however, this inference is biased given the existence of autocorrelation in the squared residuals. If we withdraw just the three most influential negative extreme values from the series, α turns out to be nonsignificant, as does the autocorrelation in the squared residuals. Facing heteroscedastic errors and the presence of highly influential observations, we carried out robust estimations on all data using Tukey's biweight loss function.[4] Although the results show nonsignificant coefficients once again, it seems that, on the last trading day, the futures market slightly overestimates the future spot price.

The weak form of the efficient market hypothesis posits that asset prices incorporate all historical information and will therefore be unpredictable in terms of any past information. In the present framework, this translates into the infeasibility of predicting the risk premium using historical information on spot prices, futures prices or any combination of the two. The obvious candidate with which we may test the predictability of the risk premium, as suggested by Ballester *et al* (2016), is the futures prices.

To test if futures prices have some predictive power in terms of the risk premium, we conjecture that, as the delivery date approaches, market agents revise their predictions of the risk premium. However, even on the last trading day, their predictions are not perfect. Accordingly, the sequence of futures prices up until the last trading day provides information about the risk premium, $\mathrm{RP}_{t,1}$. This is in accordance with Brown and Jennings (1989), who argue that a sequence of prices may be more informative than the last known price. This conjecture may be tested using the following linear regression:

$$\mathrm{RP}_{t,1} = \alpha + \beta f_{t,T} + \epsilon_{t,T}, \tag{4.7}$$

where $f_{t,T}$ is the daily logarithmic futures return,

$$f_{t,T} = \ln(F_{t,T}) - \ln(F_{t-1,T+1}). \tag{4.8}$$

The results are presented in Table 6 using futures price information for up to eleven trading days before the beginning of the delivery month.

In these regressions, α always has a significant negative value, while β is always positive; β, however, is only significant at the 1% level, for futures returns for four, five and six days prior to delivery. An explanation for this result is that most information-based trading is probably concentrated during these days.

We also check whether futures prices provide any additional information after controlling for the explanatory variables proposed by Bessembinder and Lemmon (2002). This model suggests that the electricity futures premium depends on the

[4] This estimation algorithm uses iteratively reweighted least squares with the bisquare weighting function, for a tuning constant of 4.685.

TABLE 6 Regressions of the risk premium on the daily futures returns.

	α	p-value	β	p-value	R^2
$f_{t,1}$	–0.051	0.001	2.463	0.041	0.109
$f_{t,2}$	–0.057	0.000	0.568	0.885	0.005
$f_{t,3}$	–0.053	0.001	1.281	0.069	0.022
$f_{t,4}$	–0.047	0.000	2.908	0.001	0.123
$f_{t,5}$	–0.048	0.000	2.761	0.000	0.206
$f_{t,6}$	–0.051	0.001	2.018	0.004	0.080
$f_{t,7}$	–0.058	0.000	0.527	0.334	0.004
$f_{t,8}$	–0.058	0.002	0.166	0.761	0.004
$f_{t,9}$	–0.058	0.002	0.687	0.256	0.008
$f_{t,10}$	–0.057	0.001	0.905	0.202	0.017

Equation (4.7) was estimated using OLS. The p-values presented in parentheses use the Newey–West auto-correlation–heteroscedasticity robust standard errors, with a bandwidth equal to three (the Bartlett kernel).

market expectations of the variance and asymmetry of the spot price at delivery. Given the definition of the risk premium used in this paper, its relationships to the variance and asymmetry should be positive and negative, respectively. Usually this model is tested ex post, that is, using the realized values of the variance and asymmetry of the spot price at delivery. Taking all this into consideration, we propose the following model:

$$\mathrm{RP}_{t,1} = \alpha + \beta f_{t,[3,7]} + \vartheta V[S_{t+T}] + \gamma A[S_{t+T}] + \varepsilon_{t+T}, \tag{4.9}$$

where $f_{t,[3,7]}$ is the futures logarithmic return from seven to three days prior to delivery, and $V[S_{t+T}]$ and $A[S_{t+T}]$ are the realized variance and nonstandardized asymmetry (ie, the third central moment) of the daily spot price in the month starting at $t + T$. We also estimate two restricted versions of this model, superimposing $\vartheta = \gamma = 0$ and $\beta = 0$. The estimation results presented in Table 7 show that the volatility and asymmetry coefficients are significant at the 1% level. However, the coefficient on the volatility has a negative sign, which raises certain doubts as to the applicability of the model proposed by Bessembinder and Lemmon (2002) to this data set. The unrestricted model (Model 3) has an R^2 value above 55%, implying that more than one half of the risk premium variability may be explained by the futures returns as well as the ex post variance and the ex post asymmetry of the spot price at delivery. The futures returns alone explain more than 28% of the risk premium variability (Model 1) and, even after controlling for the variance and asymmetry of the spot price, the futures returns are still significant at the 1% level.

To garner additional evidence for the previous claim, we analyze the out-of-sample predictive power of futures returns regarding the risk premium. We estimate recursively Model 1 (the first in-sample subset only covers the initial five contracts) and

TABLE 7 The in-sample fit of futures returns.

	Model 1	Model 2	Model 3
α	–0.035 (0.002)	–0.004 (0.722)	0.008 (0.490)
$f_{t,[3,7]}$	1.650 (0.000)	–	1.376 (0.000)
$V[S_{t+T}]$	–	–0.149 (0.000)	–0.130 (0.000)
$A[S_{t+T}]$	–	–0.731 (0.000)	–0.642 (0.000)
R^2	0.286	0.364	0.558

Equation (4.9) was estimated via OLS. The p-values, in parentheses, use the Newey–West autocorrelation–heteroscedasticity robust standard errors, with a bandwidth equal to 3 (Bartlett kernel). The variance and the asymmetry variables were multiplied by 10^{-2} and 10^{-4}, respectively.

TABLE 8 The out-of-sample predictive power of futures returns.

	Futures-based	Unconditional
Number of successes	83	80
Frequency of successes	0.648	0.625
Mean return	0.063	0.055
SD of returns	0.139	0.142
Sharpe ratio	0.454	0.384
Bootstrap p-value	(0.257)	

The futures-based strategy uses Model 1 of Table 7 to recursively extract the signal of the next risk premium. The first estimation uses just five contracts and, therefore, the statistics were obtained for 123 contracts. The unconditional strategy is based on the assumption that the risk premium is always negative. The Sharpe ratio is given by the division between the mean and the standard deviation. The last row shows the bootstrap p-value under the null hypothesis of equal Sharpe ratios and the alternative hypothesis that the Sharpe ratio of the futures-based strategy is greater than the Sharpe ratio of the unconditional strategy. This p-value was obtained using 10 000 bootstrap samples, created with the circular block procedure proposed by Politis and Romano (1994), with an optimal block size of two (chosen according to Politis and White 2004).

compute the one-step forecast. Then, we calculate the returns of a trading strategy that uses the signal of the risk premium forecast to devise a position in the futures market on the last trading day (assuming that these trades are feasible, that is, without considering any liquidity constraints). If the risk premium forecast is positive (negative) the strategy prescribes a long (short) position in the futures contract. This futures-based strategy is compared with an unconditional strategy that assumes the risk premium is always negative and, therefore, the trader is always short in the futures contract.

Before we compare the two strategies, it is worth noting that the measure of forecastability proposed by Granger and Newbold (1986, p. 310) for the one-step forecast of the risk premium using Model 1, given by $G = \text{var}(\widehat{\text{RP}}_{t,1})/\text{var}(\text{RP}_{t,1})$, is 0.220, implying that the goodness-of-fit of the model ($R^2 = 0.286$) is fairly well preserved out-of-sample.

Table 8 presents some results generated by the two strategies. The futures-based strategy obtains just three more successes than the unconditional strategy, resulting in an increase in the mean return and a slight decrease in the returns' standard deviation. The futures-based strategy has a Sharpe ratio that is roughly 18% above the corresponding metric for the unconditional strategy. Although the bootstrap p-value does not allow us to reject the null hypothesis that both strategies share the same Sharpe ratio, we can always argue that a difference of 0.8% in monthly mean returns is economically significant by any standards.

5 CONCLUSIONS

This paper provides an empirical analysis of the risk premium of base-load monthly futures traded on MIBEL. Certain features typical of electricity markets and attributed to the nonstorable nature of electricity and/or the reduced number of market players are also found here. We document the presence of frequent extreme values, high volatility clustering and low-frequency seasonalities (both monthly and per season of the year). The spot volatility is higher than the futures volatility, which in turn increases as the delivery month approaches. This gives some supportive evidence on the existence of the Samuelson effect in this market.

The ex post risk premium, computed as the logarithm of the ratio between the spot price at delivery and the futures price on the last trading day, is -5.77% on average, but it shows high variability. The risk premium is negatively skewed, has excess kurtosis, shows some persistence and depends on the season of the year. The amplitude of the risk premium and its volatility decreases nonlinearly with the remaining trading days until delivery.

Although we were not able to reject the unbiased forward hypothesis, we found a significant relationship between the risk premium and the futures returns. These two results seem contradictory; however, we must stress that the first result is drawn from observations of a single point in the futures price process for each contract, while the second result derives from observations of the price path near the maturity. In sum – despite the small sample size (only 128 contracts), the illiquidity of the futures market (with, on average, no more than 2.5 trades per day) and our exclusive focus on the financial aspects of the market (without any consideration for the fundamentals) – our main result is that the sequence of futures prices near delivery may provide valuable information for predicting the risk premium in the Iberian electricity market. However, the forecastability of the risk premium does not necessarily guarantee profitable speculative trading, due to the low liquidity of these futures contracts.

In light of the evidence presented here, we suggest that OMIP should pursue measures aiming to improve liquidity and to stimulate information-based speculation in the futures market. Attracting more speculative trading will result in an increase in the market liquidity, reducing the cost of hedging and improving the price discovery role of the futures market. In fact, concerns around low market liquidity, high market concentration (in 2016, according to Operador do Mercado Ibérico de Energia (2017), the biggest ten market participants held a market share of 73.6%) and low interest from international participants not involved in electricity production or consumption (such as banks and investment funds) have been outlined in all OMIP annual reports since 2010.

DECLARATION OF INTEREST

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of the paper.

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REFERENCES

Ballester, J. M., Climent, F., and Furió, D. (2016). Market efficiency and price discovery relationships between spot, futures and forward prices: the case of the Iberian electricity market (MIBEL). *Spanish Journal of Finance and Accounting/Revista Española de Financiación y Contabilidad* **45**(2), 135–153 (https://doi.org/10.1080/02102412.2016.1144441).

Benth, F. E., Cartea, Á., and Kiesel, R. (2008). Pricing forward contracts in power markets by the certainty equivalence principle: explaining the sign of the market risk premium. *Journal of Banking and Finance* **32**(10), 2006–2021 (https://doi.org/10.1016/j.jbankfin.2007.12.022).

Benth, F. E., Biegler-König, R., and Kiesel, R. (2013). An empirical study of the information premium on electricity markets. *Energy Economics* **36**, 55–77 (https://doi.org/10.1016/j.eneco.2012.12.001).

Bessembinder, H., and Lemmon, M. L. (2002). Equilibrium pricing and optimal hedging in electricity forward markets. *Journal of Finance* **57**(3), 1347–1382 (https://doi.org/10.1111/1540-6261.00463).

Botterud, A., Kristiansen, T., and Ilic, M. D. (2010). The relationship between spot and futures prices in the Nord Pool electricity market. *Energy Economics* **32**(5), 967–978 (https://doi.org/10.1016/j.eneco.2009.11.009).

Brown, D. P., and Jennings, R. H. (1989). On technical analysis. *Review of Financial Studies* **2**(4), 527–551 (https://doi.org/10.1093/rfs/2.4.527).

Bunn, D. W., and Chen, D. (2013). The forward premium in electricity futures. *Journal of Empirical Finance* **23**, 173–186 (https://doi.org/10.1016/j.jempfin.2013.06.002).

Cartea, Á., and Figueroa, M. G. (2005). Pricing in electricity markets: a mean reverting jump diffusion model with seasonality. *Applied Mathematical Finance* **12**(4), 313–335 (https://doi.org/10.1080/13504860500117503).

Cartea, Á., and Villaplana, P. (2008). Spot price modeling and the valuation of electricity forward contracts: the role of demand and capacity. *Journal of Banking and Finance* **32**(12), 2502–2519 (https://doi.org/10.1016/j.jbankfin.2008.04.006).

Cartea, Á., and Villaplana, P. (2014). An analysis of the main determinants of electricity forward prices and forward risk premia. In *Quantitative Energy Finance*, pp. 215–236. Springer (https://doi.org/10.1007/978-1-4614-7248-3_8).

European Commission (2010). Quarterly report on European electricity markets. *Market Observatory for Energy* **3**(1), 1–33.

European Commission (2013). Quarterly report on European electricity markets. *Market Observatory for Energy* **6**(2), 1–30.

European Commission (2014). Quarterly report on European electricity markets. *Market Observatory for Energy* **6**(3–4)–**7**(1–2), 1–323.

Fleten, S.-E., Hagen, L. A., Nygård, M. T., Smith-Sivertsen, R., and Sollie, J. M. (2015). The overnight risk premium in electricity forward contracts. *Energy Economics* **49**, 293–300 (https://doi.org/10.1016/j.eneco.2014.12.022).

Furió, D., and Meneu, V. (2010). Expectations and forward risk premium in the Spanish deregulated power market. *Energy Policy* **38**(2), 784–793 (https://doi.org/10.1016/j.enpol.2009.10.023).

Granger, C., and Newbold, P. (1986). *Forecasting Economic Time Series*, 2nd edn. Academic Press, Orlando, FL.

Haugom, E., and Ullrich, C. J. (2012). Market efficiency and risk premia in short-term forward prices. *Energy Economics* **34**(6), 1931–1941 (https://doi.org/10.1016/j.eneco.2012.08.003).

Haugom, E., Hoff, G. A., Mortensen, M., Molnár, P., and Westgaard, S. (2014). The forecasting power of medium-term futures contracts. *The Journal of Energy Markets* **7**(4), 1–23 (https://doi.org/10.21314/JEM.2014.108).

Herráiz, Á. C., and Monroy, C. R. (2009). Analysis of the efficiency of the Iberian power futures market. *Energy Policy* **37**(9), 3566–3579 (https://doi.org/10.1016/j.enpol.2009.04.019).

Higgs, H., and Worthington, A. (2008). Stochastic price modeling of high volatility, mean-reverting, spike-prone commodities: the Australian wholesale spot electricity market. *Energy Economics* **30**(6), 3172–3185 (https://doi.org/10.1016/j.eneco.2008.04.006).

Jaeck, E., and Lautier, D. (2016). Volatility in electricity derivative markets: the Samuelson effect revisited. *Energy Economics* **59**, 300–313 (https://doi.org/10.1016/j.eneco.2016.08.009).

Lagarto, J., Sousa, J., Martins, A., and Ferrão, P. (2012). Price forecasting in the day-ahead Iberian electricity market using a conjectural variations ARIMA model. In *9th International Conference on the European Energy Market*, pp. 1–7. Institute of Electrical and Electronics Engineers, New York (https://doi.org/10.1109/EEM.2012.6254734).

Lucia, J. J., and Torró, H. (2011). On the risk premium in Nordic electricity futures prices. *International Review of Economics and Finance* **20**(4), 750–763 (https://doi.org/10.1016/j.iref.2011.02.005).

Miranian, A., Abdollahzade, M., and Hassani, H. (2013). Day-ahead electricity price analysis and forecasting by singular spectrum analysis. *IET Generation, Transmission and Distribution* **7**(4), 337–346 (https://doi.org/10.1049/iet-gtd.2012.0263).

Monteiro, C., Fernandez-Jimenez, L. A., and Ramirez-Rosado, I. J. (2015). Explanatory information analysis for day-ahead price forecasting in the Iberian electricity market. *Energies* **8**(9), 10464–10486 (https://doi.org/10.3390/en80910464).

Operador do Mercado Ibérico de Energia (2017). OMIP annual report 2016. Report, OMIP. URL: https://bit.ly/2Loo2S5.

Pietz, M. (2009). Risk premia in the German electricity futures market. In *3rd International Conference on Energy and Environment*, pp. 160–170. Institute of Electrical and Electronics Engineers, New York (https://doi.org/10.1109/ICEENVIRON.2009.5398651).

Pirrong, C., and Jermakyan, M. (2008). The price of power: the valuation of power and weather derivatives. *Journal of Banking Finance* **32**(12), 2520–2529 (https://doi.org/10.1016/j.jbankfin.2008.04.007).

Politis, D. N., and Romano, J. P. (1994). The stationary bootstrap. *Journal of the American Statistical Association* **89**(428), 1303–1313 (https://doi.org/10.1080/01621459.1994.10476870).

Politis, D. N., and White, H. (2004). Automatic block-length selection for the dependent bootstrap. *Econometric Reviews* **23**(1), 53–70 (https://doi.org/10.1081/ETC-120028836).

Redl, C., and Bunn, D. W. (2013). Determinants of the premium in forward contracts. *Journal of Regulatory Economics* **43**(1), 90–111 (https://doi.org/10.1007/s11149-012-9202-7).

Redl, C., Haas, R., Huber, C., and Böhm, B. (2009). Price formation in electricity forward markets and the relevance of systematic forecast errors. *Energy Economics* **31**(3), 356–364 (https://doi.org/10.1016/j.eneco.2008.12.001).

Shawky, H. A., Marathe, A., and Barrett, C. L. (2003). A first look at the empirical relation between spot and futures electricity prices in the United States. *Journal of Futures Markets* **23**(10), 931–955 (https://doi.org/10.1002/fut.10093).

Umutlu, G., Dorsman, A., and Telatar, E. (2011). The electricity market, day-ahead market and futures market. In *Financial Aspects in Energy: A European Perspective*, Dorsman, A., Westerman, W., Karan, M. B., and Arslan, Ö. (eds), pp. 109–128. Springer (https://doi.org/10.1007/978-3-642-19709-3_7).

Weron, R., and Zator, M. (2014). Revisiting the relationship between spot and futures prices in the Nord Pool electricity market. *Energy Economics* **44**(C), 178–190 (https://doi.org/10.1016/j.eneco.2014.03.007).