The Iberian Electricity Market: Price Dynamics and Forward Risk Premium

Dissertação de Mestrado em Métodos Quantitativos em Finanças, orientada pelo Professor Doutor Helder Miguel Correia Virtuoso Sebastião e apresentada ao Departamento de Matemática da Faculdade de Ciências e Tecnologia e à Faculdade de Economia da Universidade de Coimbra.

5 de Abril de 2017

· U C ·

UNIVERSIDADE DE COIMBRA

The Iberian Electricity Market: Price Dynamics and Forward Risk Premium

Márcio Rafael Baptista Ferreira

· U C ·

Universidade de Coimbra
Master in Quantitative Methods in Finance
Mestrado em Métodos Quantitativos em Finanças

MSc Dissertation | Dissertação de Mestrado

April 2017

Acknowledgements

I would like to express my gratitude to my advisor Prof. Dr. Helder Sebastião for the guidance and support throughout this thesis. I am grateful to my parents and friends for their affection and support.

Abstract

The appearance of electricity exchanges has attracted much attention on the price formation mechanism. There is an increasing interest in the relationship between futures and spot electricity prices. This work provides an empirical analysis of electricity spot and futures markets of the Iberian Electrical Energy Market. The used dataset covers the period from 1 March 2006 to 30 September 2016 and incorporates 123 monthly futures contracts. The determination of the ex-post risk premium and the analysis of its properties were performed. We obtained a time dependent risk premium that fluctuates between positive and negative values, resulting in the high volatility value of 18.094% of its distribution. We concluded that futures contracts were traded on average at 7.54% above the spot prices, meaning that the market agents are willing to pay a higher price for futures contracts in order to reduce their risk exposure. We found a decreasing non-linear dependence of the average risk premium as the futures contract maturity approaches. We obtained statistical indications for rejecting the unbiased forward hypothesis of the futures contracts prices near maturity. Finally, we considered the weak-form efficient market hypothesis, analyzing the predictability of the risk premium. We looked for information about the risk premium contained on the futures bases, spot returns, and futures returns. We obtained indications that the futures return near maturity contains information on the risk premium.

Resumo

O surgimento de mercados organizados de eletricidade tem atraído muita atenção para o mecanismo de formação de preços. Existe um interesse crescente sobre a relação entre os preços dos futuros e os preços spot. Este trabalho fornece uma análise empírica dos mercados spot e de futuros pertencentes ao Mercado Ibérico de Energia Elétrica. A base de dados usada abrange o período de 1 de Março de 2006 a 30 de Setembro de 2016 e incorpora 123 contratos de futuros mensais. Foi determinado o prémio de risco ex-post e realizada uma análise das suas propriedades. Obtivemos um prémio de risco dependente do tempo que oscila entre valores positivos e negativos, resultando no valor elevado de 18.094% para a volatilidade da sua distribuição. Concluímos que os contratos de futuros foram transacionados em média a 7.54% acima do valor do mercado spot, significando que os agentes do mercado estão disponíveis para pagar um preço elevado pelos contratos de futuros por forma a reduzir a sua exposição ao risco. Encontrámos uma dependência decrescente não-linear do prémio de risco médio com a aproximação da maturidade do contrato. Obtivemos indicações estatísticas para rejeitar a hipótese de não enviesamento futuro dos preços dos contratos de futuros próximos da maturidade. Finalmente, considerámos a hipótese de eficiência do mercado na sua forma fraca, analisando a previsibilidade do prémio de risco. Procurámos informação sobre o prémio de risco contida nas bases dos contratos de futuros, nas rentabilidades do mercado spot e nas rentabilidades do mercado de futuros. Obtivemos indicações de que o retorno do mercado de futuros próximo da maturidade contém informações sobre o prémio de risco.

Table of contents

List of figures

List of tables

Chapter 1

Outine

The relationship between futures and spot electricity prices has attracted the attention of both finance academics and market participants. Due to the worldwide deregulation of electricity markets and to the creation of electricity exchanges, the mechanism of price formation is of great importance an is still under debate.

In this work we analyze the relationship between electricity spot and futures prices, based primarily on risk considerations. This work provides an empirical analysis of the behavior over time of the futures risk premium, by studying the monthly futures contracts traded at the Iberian Energy Derivatives Exchange.

This thesis is organized as follows: we give a brief introduction to the basic structure of electricity markets in Chapter 2, where we explain the main distinguishable characteristics of electricity among other energy commodities; then, an overview of both the spot and futures markets of the Iberian electricity market is present in Chapter 3; two theories for valuation futures prices, namely the Cost-of-Carry and the Hedging Pressure theories, are described in Chapter 4; in Chapter 6 we made a description of the used data set; the results are presented both for spot and futures prices in Chapter 7; and, finally, the conclusions are drawn in Chapter 8.

Chapter 2

Introduction to Electricity Markets

The electricity markets belong to a wider group of energy markets. The fuel markets, e.g., oil, gas, coal and their byproducts, are the oldest energy markets at the wholesale level. Recently, underlying assets related to electricity, e.g., weather and emissions, lead to the formation of new energy markets.

Bellow, we give a brief overview of the electricity market structure, showing some of its distinctive characteristics from other energy markets. We follow the references [1–3]. Therein, the reader can find a detailed discussion of the following topics.

2.1 Non-storability

The central feature that distinguishes electricity from other commodities is storage. Contrary to electricity, most commodities can absorb sudden production and demand variations by storage. Thus, generally, we can assume that electricity supply and demand must be in equilibrium at every time. Actually, electricity can be stored, but not in the form of electric current. It can be converted into other storable form of energy, which allows future transformation into electric current. As an example, electric current might be used for pushing water to a pumped storage that, at later time, can be converted back to electric current by hydro power. This and other storage methods have, however, high costs and low efficiencies. Therefore, when we say that electricity is non-storable, we mean that, at the present time, it is financially infeasible.

2.2 Electricity supply stages

The non-storable characteristic of electricity is singular among other commodities. The efficiency of electricity markets is thus a challenging task, requiring additional balancing services and reserve resources, beyond the common production and distribution services.

The essential stages in the supply chain of electricity are generation, transmission, and balancing services.

The generation of electricity starts with its energy source, which can be fossil fuels (coal, oil, and natural gas), renewable energy (mainly hydroelectric, wind, geothermal, and solar), nuclear power, and other sources, e.g., bio-fuels and biomass. The energy source might need further processing and refining before it enters into the power generation, i.e., the process by which the energy source is converted into electricity. The next step is delivering the electricity into the distribution infrastructure.

The electricity generation is nowadays dominated by the following technologies: nuclear, coal-steam, gas/oil-steam, combined cycle, combustion turbine, hydro, and renewals. Different countries have distinct mixes of technologies. A generation unit is mainly specified by its daily generation profile, the marginal cost per MWh that is prepared to sell, and both the profile of the daily maximum capacity and minimum stable generation. The electricity provided by power generators is normally classified by a load factor. A base-load plant runs continuously with a steady load, although some plants can provide with load variations to add to system stability and reserve capability. A peaking plants are expected to run at certain periods of time. They have a reserve function to cover events such as demand spikes or sudden outages.

Due to the absence of storage capability and the very low level of dynamic response of power generators, the amount of electricity produced must be, at every instant, equal to the amount of power consumed. An extremely high level of flexibility, e.g., short term response in time and volume, is required from power generators to deal with sudden variations in demand and both generator and network failures.

The electricity supply industry is driven by the time-space character of electricity: it is instantaneously delivered over very long distances with high variations in the delivery rate. Network considerations such as inefficiencies, electric resistance, and electric reactance are crucial in the design of electricity markets. Transmission lines, distribution lines, transformers, and other equipment are needed to transmit and distribute electricity.

The balancing services are mainly insured by the system and market operators. The system operator is the energy management of the system, which guarantees the perfect and continuously equilibrium of demand and supply, and also the stability of the network transmission. Market operations involve the commercial arrangements for energy and trading capacity between participants and the system operator.

2.3 The Wholesale Market

Conventional markets do not require any special organization, i.e., there is no central coordination between buyers and sellers. The organization of electricity markets is, however, essential to ensure the perfect matching of supply and demand at any given moment. Any demand variation within a day, hour or even minute must be perfectly balanced by supply. Any imbalance between supply and demand can be very costly, and may lead to wide-ranging blackouts.

In day-ahead markets, electricity is traded for every hour of the following day, and can be seen as a forward market with delivery on the following day. Using the day-ahead market information, the system operator establishes which generating units should be scheduled and dispatched to meet demand in every hour of the following day in the most economic way. The actual demand and generation capacity may change near to the real time of delivery, and adjustments to the day-ahead schedules may be required. This is accomplished through the intra-day markets (also known as real-time balancing markets), where buyers and sellers can adjust their positions hours and minutes before the operation taken place. These adjustments are made by changing the dispatch of generators committed in the day-ahead market.

The day-ahead markets are organized with different centralization degrees: bilateral markets, exchanges, and pools.

In the bilateral markets, trades are established directly between buyers and sellers, without any external coordination. These bilateral trades are then collected by the transmission operator, which is an external entity that ensures their technical feasibility, i.e., the physical delivery will not overload any transmission lines or other equipment on the system.

A power exchange is a centralized market that gathers simple price–quantity demand bids and supply offers during each hour of the following day. Then exchanges determine the market-clearing quantity by intersecting supply and demand curves. The market-clearing price is typically unique, being paid by all cleared bids to all cleared offers.

The pools differ from exchanges mainly by accepting more complex bids from generators. Besides the price, bids may also include start-up costs, no-load costs, ramp rates, and minimum run times. The generation is scheduled to meet the system demand by minimizing the total ask-bid, by setting the price at the last accepted bid price. Even though the clearing price may not always be enough to cover the start-up and no-load costs, the generation units may be scheduled to operate. When this occurs, the pool provides side payments to ensure that the scheduled generation receives an economic profit.

Within bilateral markets, the participants can adjust the terms of the contract according to their individual needs. However, bilateral trades can be established alongside organized pools or exchanges using contracts for differences. On the other hand, bilateral markets have inefficient generation scheduling and disadvantages in management of transmission constraints. Efficiency is best attained by the coordination of power pools, which simultaneously observes all power schedules, generators unit commitment costs, and available transmission capacity. Having a middle degree of centralization, between bilateral markets and pools, power exchanges share some benefits and drawbacks of both, e.g., some elements of explicit transmission congestion management are present.

Chapter 3

The Iberian Electricity Market

The Iberian Electrical Energy Market (MIBEL) is a joint wholesale electricity market between Spain and Portugal. The agreement between both countries was signed on 1 October 2004. The agreement established the framework and organization of both a spot and a derivatives markets. MIBEL was fully launched on 1 July 2007.

Herein, we provide a brief overview of the main properties of both spot and derivatives markets of MIBEL. A detailed and complete information can be found in [4, 5].

3.1 Spot Market (OMIE)

The wholesale spot market allows for electricity trades between market agents. Buyers are reference retailers, re-sellers, and direct consumers, while sellers are electricity power producers The spot market is managed by the Spanish division of the Iberian Energy Market Operator (OMIE). The OMIE regulates two complementary markets: the daily and the intra-day markets.

The daily market sets the electricity prices for the twenty-four hours of the following day, i.e., the day-ahead. On a daily basis, purchase and sale orders are received in the daily market. The electricity price and volume are determined by the equilibrium between supply and demand for each hour of the day-ahead. The equilibrium is determined by the marginal pricing model.

When the traded electricity overcomes the total capacity of the electrical interconnection network between Spain and Portugal, a market splitting mechanism sets in, and different electricity prices take place on Portugal and Spain daily markets. When the interconnection network is not congested, both Spain and Portugal daily markets have the same prices.

The results from the daily market are evaluated by the system operator, which ensures their technical viability. If required, changes are conducted by the System Operator and a final viable daily schedule is established.

3.1.1 Intra-day market

Adjustments to the final viable daily schedule are possible via the intra-day market, where market agents can adjust their positions some hours earlier to the delivery time. All market agents that have participated in the corresponding daily market session or have executed a physical bilateral contract may participate in the intra-day market.

Once the daily market closes, six intra-day markets sessions are held, where market agents can adjust their positions up to four hours ahead of real time delivery. The adjustments in each session are made by submitting bids for the purchase and sale of electricity. The market operator matches the demand/supply, obtaining for each hour in the schedule a marginal price and volume of electricity accepted for each production.

3.2 Derivatives market (OMIP)

The Operador do Mercado Ibérico de Energia – Pólo Português, S.G.M.R., S.A. (OMIP) is the energy derivatives market of MIBEL, and is responsible for organizing and managing the derivatives market. The derivatives contracts traded in OMIP are futures, options, swaps, and other forward contracts, whose underlying asset is electricity. Contracts have either physical or purely financial delivery during the delivery period of the contract: in the former there is a physical settlement, while the latter is subject to an exclusive financial settlement. There are base and peak derivative products. The delivery period of base derivatives covers all daily hours, while peak derivatives only covers peak hours (typically from 8a.m. to 7p.m.).

The OMIClear performs the role of the clearing house, central counter-party, and Settlement system. Bilateral transactions are also registered trough OMIClear.

Two trading modes coexist within OMIP [6]: the continuous market and the call auction. The continuous trading is the default trading mode, in which anonymous buy and sell orders match immediately, generating trades with an undetermined number of prices for each contract. Buy orders with the highest prices and sell orders with the lowest prices are executed first. In the call auction trading, a single-price auction maximizes the traded volume, with all trades being settled at the same price. It uses an algorithm based on the maximum tradable volume and minimum price criteria.

3.2.1 Futures Contracts

There are different futures contracts traded on OMIP that are identified by their delivery periods: day, weekend, week, month, quarter, and year. For each futures contract there are base and peak loads with financial or physical settlement. The underlying asset of each contract is the notional supply/receiving of electric energy at a constant power of 1 MWh, during all hours of the delivery period. Furthermore, the underlying asset is evaluated daily on the delivery period, based on the spot reference price. Base and peak load with financial or physical settlement contracts are quoted in euros per MWh. The futures contracts are specified by: first trading day, last trading day (the trading day preceding the first delivery day), first delivery day, last delivery day, trading period, and delivery period. The trading period of a contract begins on the first trading day and ends on the last trading day. On the other hand, the delivery period is the time between the first delivery day and the last delivery day.

Trading is conducted in continuous mode, auction mode, or through bilateral transactions, being subsequently registered at the OMIClear. To protect the position exposure of the clearing members, the OMIClear identifies and collects the margins on a daily basis. For futures contracts, the main cash settlements executed by the OMIClear are the variation margin and the delivery settlement value. In the former, the profits and losses in tradable contracts are covered by daily cash settlements, and the latter covers the settlement risk originated from open positions in contracts under delivery.

After the closing of each trading session, the OMIP defines the settlement price for each contract. At the end of the last trading day session of each contract, the open positions are deemed final for settlement on the delivery period, being subject, on a daily basis, to a purely financial settlement by the OMIClear. During the delivery period, the spot reference price is the value of the PTEL or SPEL base/peak indexes[1]. On a daily basis, the OMIClear processes the financial settlement of the delivery settlement value, which results from the difference between the spot reference price and the settlement price of each contract on the last trading day, having as underlying the notional supply/receiving of electric energy at a constant power for the number of hours of each day of the delivery period. Furthermore, for physical settlements contracts the positions are submitted to the spot market (OMIE) as limit prices orders.

[1]Note that the PTEL and SPEL indexes are only different when the market splitting mechanism sets in.

Chapter 4

Futures Pricing

There are two theories that explain how equilibrium prices of futures contracts are determined for general commodities. The first theory is the well known cost-of-carry model [7]. The second one is the hedging pressure theory [8]. The former is applied for storable commodities, and the latter to storable and non-storable commodities, such as electricity.

Below, we give a brief description of both theories. We follow the reference [9], where the reader can find a detailed discussion.

4.1 Cost-of-Carry

For a certain futures contract, let us assume that there is no cost of storing the underlying commodity, and there is neither dividends nor additional profit from its storage. Then, the cost-of-carry theory tells us that the market price of the futures contract at time t is

$$F(t,T) = S(t)e^{r(T-t)}, \tag{4.1}$$

where $S(t)$ is the value of the underlying commodity at time t, r gives the time-independent risk-free rate, and T is the maturity of the futures contract.

Storage costs affect the futures price, and can be taken into account as

$$F(t,T) = S(t)e^{(r+q)(T-t)}, \tag{4.2}$$

where q is the continuous rate of storage costs. Additionally, in the presence of any yields from owning the commodity, known as convenience yield, the cost-of-carry model is given by

$$F(t,T) = S(t)e^{(r+q-c)(T-t)}, \tag{4.3}$$

where c is the continuous convenience yield.

The cost-of-carry equations are deduced from arbitrage-free arguments, being the above price the only one that does not allow arbitrage opportunities. Note that the model is only applicable to commodities that can be stored. The cost-of-carry model does not have any application in terms of risk premium.

4.2 The Theory of Hedging Pressure

Since electricity cannot be stored, an alternative approach is needed to evaluate the electricity futures contracts. The theory of hedging pressure applies to storable and non-storable commodities, and thus is applicable to to futures electricity markets. Within this theory, futures contracts are instruments to hedge away price risk, as they protect against future price changes of the underlying asset. The futures contract plays a similar role of an insurance contract: the insured agent pays a premium to eliminate future (price) risk. Therefore, the futures contract price reflects the expected price of the underlying asset at the future delivery date and the risk premium.

Like in an insurance contract, the expected risk premium is the price associated with the transfer of risk between agents involved in the exchange of futures contract. Thus, the risk premium is the price that the hedgers are willing to pay to hedge away their exposure to price volatility. Conversely, the risk premium is the compensation required by the agent who is willing to take the price risk.

The sign of the risk premium will depend on whether the hedgers are mainly producers or consumers. If the hedgers are mainly producers, there is a negative risk premium: the producers are willing to sell their expected production at a fixed price, lower than the expected future spot price. The producers are willing to obtain a lower profit, by paying the risk premium to hedge away the spot price risk. On the other hand, if hedgers are mainly consumers, then the risk-free premium would be positive: the consumers are willing to buy their expected electricity needs at a fixed price, higher than the expected future spot price. Therefore, the consumers are willing to pay a higher price, associated with the risk premium, to hedge away the spot price risk. Thus a positive (negative) risk premium means that the hedger accepts a higher (lower) future price than the expected spot price.

During periods of high demand, when the volatility is high and the occurrence of spikes is probable, consumers are more willing to pay a positive risk premium. Producers, however, may prefer not to be exposed to (potential) positive price shocks and be less inclined to offer cover, i.e., sell futures contracts. Thus, during periods of intense volatility of spot prices is may be very expensive to hedge away risk. During these high-risk premium periods, the speculators have the important role of making the market more competitive, pushing the risk premium to lower values. The risk premium is thus the price associated with the transfer of risk between speculators and hedgers.

4.3 The Forward Risk Premium

By the theory of hedging pressure, forward contract price can be split into the expected price of the underlying asset on the maturity and a risk premium, also known as forward or futures premium.

The forward risk premium is normally defined as ex-ante or ex-post. The ex-ante is defined as the difference between the forward price and the expected price of the underlying asset. As the expected price is not directly observable from market data, the ex-ante requires a model for the dynamics of the underlying asset. Therefore, different models will generally result in different values for the expected price of the asset, and thus in distinct values for the ex-ante risk premium.

On the other hand, the ex-post forward premium is defined as the difference between the forward and the realized spot price at the maturity period of the contract.

The forward ex-ante and ex-post risk premium are defined, respectively, by

$$RP_{t,T}^{\text{ex-ante}} = F_{t,T} - \mathrm{E}_t[S(T)], \tag{4.4}$$
$$RP_{t,T}^{\text{ex-post}} = F_{t,T} - \bar{S}_T, \tag{4.5}$$

where $F_{t,T}$ stands for the futures price at day t with future delivery time period of T, and $\bar{S}_T$ denotes the realized average spot price over the delivery time period T. The operator $\mathrm{E}_t[.]$ represents conditional expectation at time (day) t. The ex-post risk premium can be written as the ex-ante forward premium plus the forecast error,

$$\begin{aligned} RP_{t,T}^{\text{ex-post}} &= F_{t,T} - \bar{S}_T \\ &= F_{t,T} - \mathrm{E}_t[S(T)] + \mathrm{E}_t[S(T)] - \bar{S}_T \\ &= RP_{t,T}^{\text{ex-ante}} + \{\mathrm{E}_t[S(T)] - \bar{S}_T\}. \end{aligned}$$

The difference between the expected and the realized commodity price during the delivery period, $\mathrm{E}_t[S(T)] - \bar{S}_T$, represents the forecast error. Generally, the forecast error is assumed to be a random white noise, and therefore the ex-post risk premium is a good proxy for the ex-ante risk premium. Evidence of a nonzero ex-post risk premium is also evidence of a nonzero ex-ante risk premium.

Chapter 5

State of the art

Several models have been proposed in the literature for the dynamics of the risk premium. An equilibrium model for the risk premium was introduced in [10], in which the risk premium is a function of the variance and skewness of the spot prices. A mean-reverting jump diffusion model for the electricity spot price was derived in [11], and a closed-form for the forward premium was then obtained. The model was applied to the electricity market of England and Wales. A model function of demand and capacity for the wholesale electricity prices was proposed in [12]. Using a two-state price model that depends on demand (load) and fuel price, the risk premium from the Pennsylvania-Jersey-Maryland electricity power pool was studied in [13].

There are several empirical studies that evaluated the relation between spot and futures prices of electricity, and the presence of risk premium. The risk premium dynamics for the German electricity market was studied in [14]. It was shown that the risk premium exhibits a term structure, which can be explained by the combination of risk aversion of market agents, and how the market power of producers, relative to that of buyers, affects forward prices with different delivery periods. Market efficiency is analyzed for the Iberian futures markets and other European power markets trough the presence of risk premium in [6]. The study concludes the present of risk premium in all markets, and thus no noticeable level of market efficiency was found. The sign and magnitude of the risk premium was found to depend on both the unexpected variation in demand and in the hydroelectric capacity for the Spanish Electricity market [15]. The forward premium turned out to be negatively related to the variance of spot price. The risk premium in Nord Pool electricity market was studied in [16]. It was found the existence of risk premium that varies significantly throughout the year, but positive on average. Some links between risk premium and both the variance and skewness of electricity spot prices were seen, providing some support for the model [10]. The effect of fundamental, behavioral, dynamic, market conduct and shock components, on electricity forward market European Energy Exchange was conducted in [17]. The impact of forward electricity prices and the relationship between forward and future spot prices is addressed in [18], for the European Energy Exchange (EEX) and the Nord Pool

Power Exchange. It was found the skewness of spot prices is significant determinant of the baseload futures-spot bias at the EEX, whereas the variance of spot prices positively influences premium in peak load. Future contracts for delivery in Germany traded at the EEX show evidence of significant positive risk premium at the short-end [19]. Futures from the Amsterdam Power Exchange – European energy Derivatives Exchange indicate that futures prices are not unbiased predictor of the future spots, and thus the presence of risk premium [20]. An empirical analysis of futures prices on New York Mercantile Exchange supports the presence of risk premium [21].

Chapter 6

Data description

We use daily spot and futures prices extracted from OMIP [5]. The data-set covers the period from 1 March 2006 to 30 September 2016. Both spot and futures prices correspond to the Spanish zone of the Iberian Electricity Market. The spot reference price[1] is the daily SPEL Base index, which corresponds to the arithmetic mean of hour marginal prices of the Spanish system for the 24 hours of the day. We consider the MIBEL SPEL base load futures contracts with monthly delivery period[2]. The futures prices correspond to the settlement prices, which are fixed on a daily basis by OMIP for each contract traded on the market. Our data-set incorporates 123 monthly SPEL base load futures contracts.

The analysis presented in this work is performed in R [22, 23].

6.1 Future Market Liquidity

Among the SPEL Base Load futures traded in the OMIP Derivatives Market, the month contracts have the highest liquidity. We confirm this by the histogram in Fig. (6.1), in which we calculate the number of traded contracts by delivery period.

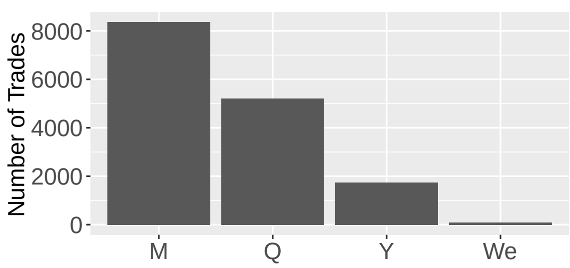

Fig. 6.1 Number of traded contracts by delivery period: Week (We), Month (M), Quarter (Q), and Year (Y).

[1]The price considered by OMIClear for calculation of the settlement amount on delivery.
[2]The period following the trading period on which the financial settlement or physical delivery of the electricity is processed.

Therefore, due to the highest liquidity, we focus on the monthly contracts in this work. Let us now analyze the trading volume and the number of trades as a function of trading days to maturity for monthly contracts. Number of trades is the number of transactions that were placed on a contract during a given period of time, and indicates the activity of a contract. Trading volume is the total quantity of contracts traded during a given period of time, measuring the total number of contracts transacted and gives information about the contracts' liquidity. A contract with higher traded volume indicates higher liquidity. To determine averages over all contracts, we synchronize the contracts at maturity.

6.1.1 Number of trades

We start by constructing the two histograms shown in Fig. 6.2: the average number of trades per trading day by contract delivery period (left panel) and total number of trades by contract delivery period (right panel). The right histogram gives the accumulated number of trades during all the trading period, and shows that the most traded futures contracts are December, November, and June month contracts. Since the trading period lengths of the contracts are different, the left histogram displays the average number of trades per trading day. It shows that only December and November contracts have more one trade per trading day on average.

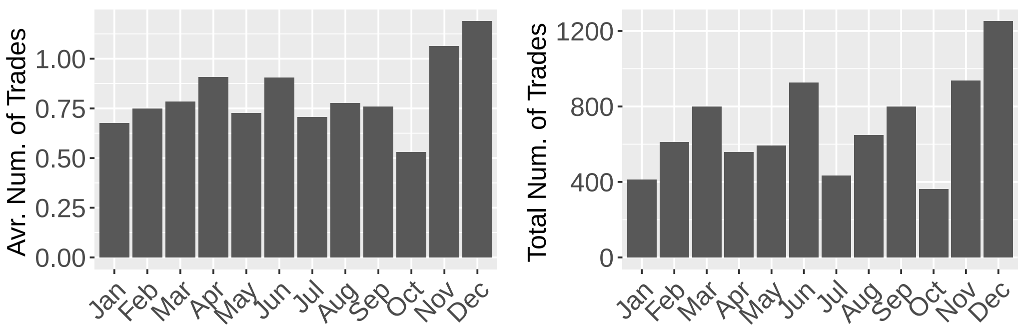

Fig. 6.2 Average number of trades per trading day (left panel) and total number of trades (right panel) by contract delivery period for the years 2007-2016.

It is worth to analyze the distribution of trades along the trading period for some specific contracts. Thus, we select the two most traded contracts and represent their number of trades as a function of the trading days in Fig. 6.3. Interestingly, the period of time with higher number of trades is near 10 and 20 days to maturity for both contracts.

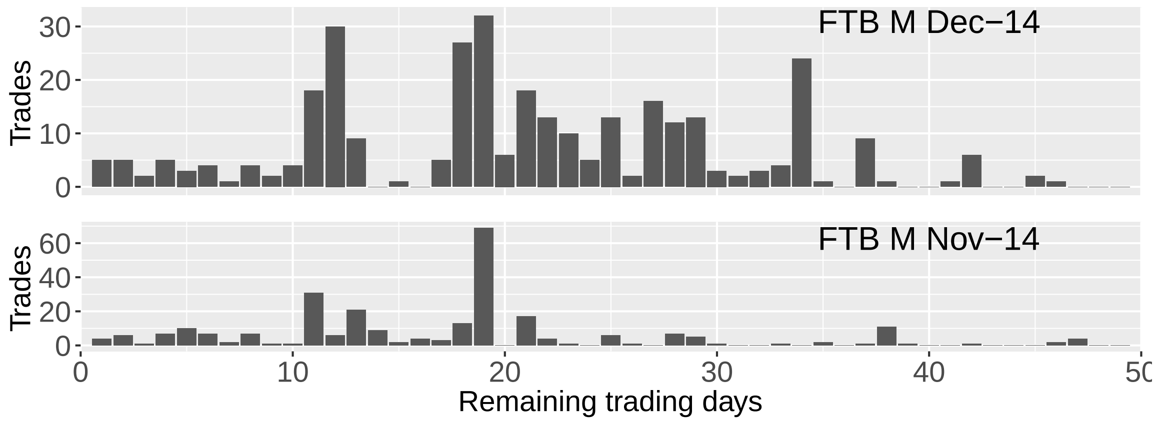

Fig. 6.3 Number of trades for the December 2014 (top) and November 2014 (bottom) contracts as a function of trading days to maturity.

To get an overall behavior, we must do an average over all contracts. The result is in Fig. 6.4. As expected, the average number of trades increases gradually as we approximate the contracts' maturity. Even though the monthly contracts are the most active contracts in the futures market (see Fig. 6.1), their average number of trades are, however, very low, reflecting the low liquidity of the futures market.

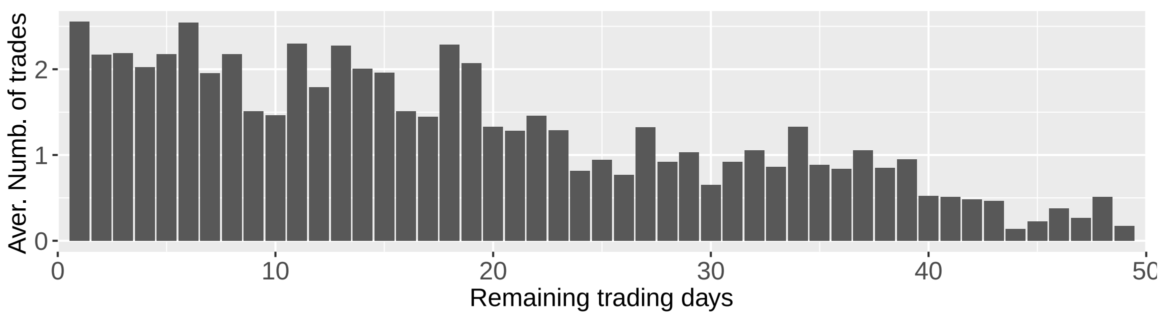

Fig. 6.4 Average number of trades over all contracts as a function of trading days to maturity.

Traded Volume

Now, we perform the same analysis, but for the contracts traded volume. Fig. 6.5 shows the average traded volume per trading day (left panel) and total traded volume (right panel) by contract delivery period. Unsurprisingly, the contracts with higher traded volume match the ones with higher number of trades.

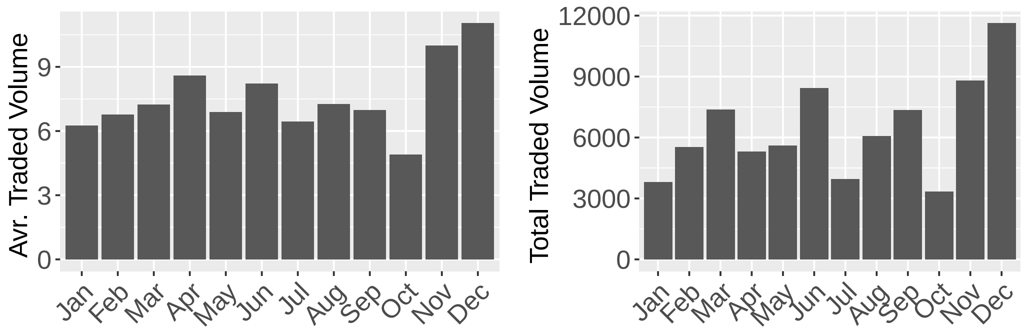

Fig. 6.5 Average traded volume per trading day (left panel) and total traded volume (right panel) by contract delivery period for the years 2007-2016.

Let us now analyze the trading volume as a function of days to maturity for the same contracts, i.e., November and December 2014. The result is in Fig. 6.6. Almost all the traded volume is concentrated on the 19th day to maturity for the November 2014 contract. On the other hand, there is some dispersion of the traded volume for the December 2014 contract.

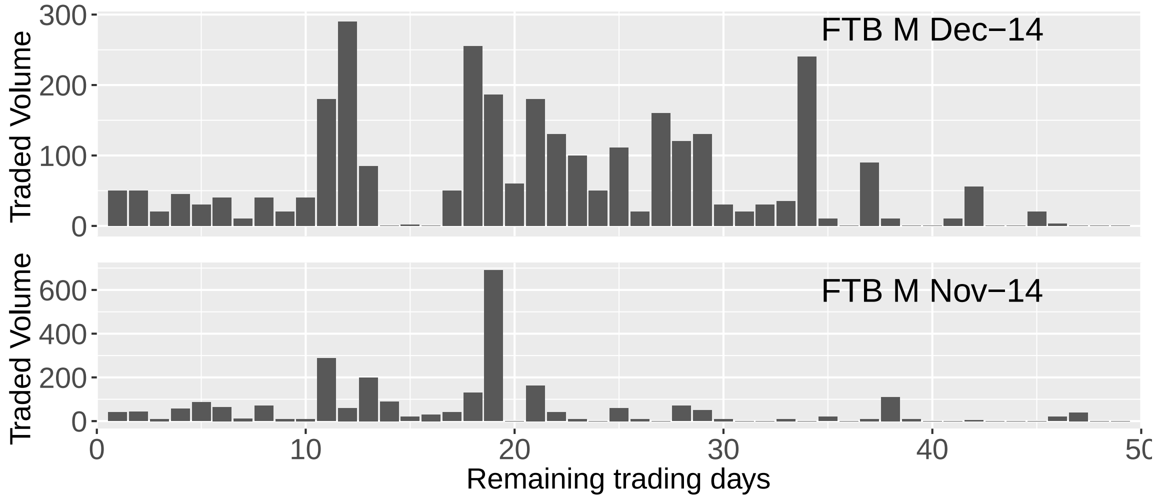

Fig. 6.6 Traded volume for the December 2014 (top) and November 2014 (bottom) contracts as a function of trading days to maturity.

The average traded volume over all contracts is in Fig. 6.7. The traded volume increases along the trading period of the contract. As for the average number of trades, the average traded volume is higher near the contracts' maturity.

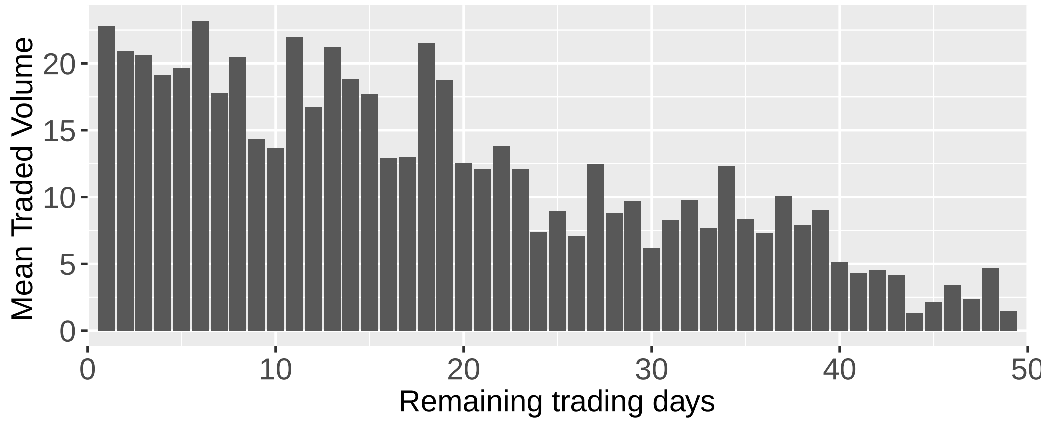

Fig. 6.7 Average traded volume over all contracts as a function of trading days to maturity.

6.1.2 Futures prices series

We define three time series for the futures prices, corresponding to 1-month ahead, 2-month ahead, and 3-month ahead. To illustrate how they are constructed, we show in Fig. 6.8 several month contracts that were traded in 2015. There are always six open contracts for trading with delivery periods corresponding to the next 6-month ahead. In the following, we focus on the first 3-months ahead contracts. The terminology used can be clarified through the following example: if we are considering some trading day in September 2015, the 1-month ahead price corresponds the Out 15 contract price (pink color), with delivery period in October 2015; the 2-month ahead price is given by the Nov 15 contract price (purple color), with delivery period on November 2015; finally, the 3-month ahead price is the Dec 15 contract price (gold color), with delivery period in December 2015.

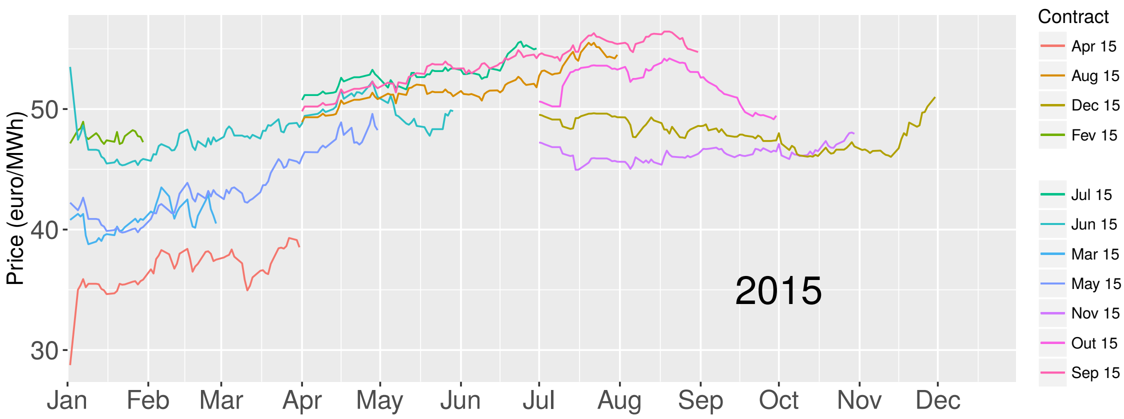

Fig. 6.8 Prices of the futures contracts traded in 2015 with delivery period in 2015.

In the next Chapter these three futures prices series will be analyzed.

Chapter 7

Results

In this Chapter, both the spot and futures prices are analyzed and their statistical properties are studied.

7.1 Spot Market

Herein, we analyze the daily electricity spot price variation given by the daily SPEL Base Load index, obtained via the arithmetic mean of hour marginal prices of the Spanish system for the 24 hours of the day. Figure 7.1 shows the spot price dynamics.

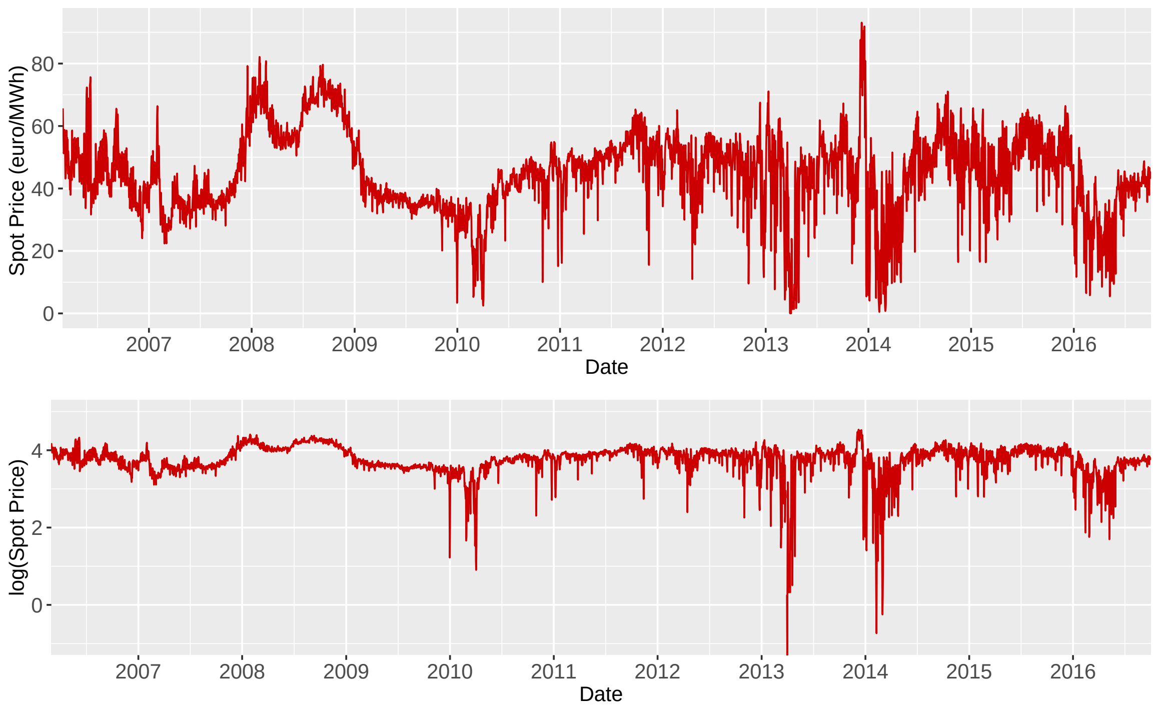

Fig. 7.1 Daily electricity prices (top), in units of €/MWh, and the logarithm of daily prices (bottom) traded for the day-ahead on MIBEL, over the time period of 1 March 2006 to 30 September 2016.

We notice some typical properties shared by all electricity markets: temporary spikes, frequent extreme values, and a high volatility levels and clustering. These features are often attributed to both the non-storable nature of the electricity and reduced number of market players. The high volatility of spot prices results from the inability to smooth supply/demand via inventories. The extreme volatility is a well known attribute of electricity markets [24].

Due to the non-storable property of electricity, periods of extreme demand lead to the occurrence of spikes on spot prices. Spikes are defined as suddenly events that occur for short period of time, leading to extreme fluctuations in the spot prices. Looking at the logarithm of spot prices (Fig. 7.1, bottom panel), we notice a mean-reversion characteristic, i.e., the price tends to fluctuate around a long-term equilibrium value. The mean-reversion of spot prices is also a common attribute of electricity markets.
Table 7.1 shows some statistical quantities of spot prices.

	Spot Price
Maximum	93.110
Day	2013-12-08
Minimum	0.0000
Day	2013-04-01
Mean	45.405
Std. Dev.	13.683
Kurtosis	3.9140
Skewness	−0.1549
JB statistic	153.16
p-value	0.0000
ADF statistic	−5.9112
p-value	< 0.0100
PP statistic	−431.55
p-value	< 0.0100

Table 7.1 Descriptive statistics for the daily spot prices. The Jarque-Bera (JB) statistic is used to test the normality of spot prices: being the null hypothesis (H_0) of normality tested against the alternative hypothesis (H_1) of non-normality. Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) statistics are useful to check for the presence of unit roots: both test the null hypothesis (H_0) of presence of an unit root against the alternative hypothesis (H_1) of no unit root.

The sample mean is 45.405€/MWh, being 93.11€/MWh the highest value, which happened on 8 December 2013. The standard deviation value of 13.683€/MWh reflects the high volatility of spot prices. The negative skewness indicates more persistent downward spikes in spot prices. Forecast these abrupt and partially unanticipated extreme changes remains an important challenge in electricity markets.

The normality of a distribution can me measured by the the Jarque-Bera statistic. Stationarity of a time series is often analyzed trough several statistical tests. We use both the Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) statistics. The test results for the spot prices are reported in Table 7.1. By the Jarque-Bera statistics, we reject the null hypothesis of distributional normality at the 0.01 level. The ADF and PP statistics allows us to reject the null hypothesis of a unit root at the 0.01 level, and thus the spot prices are stationary.

Weather conditions strongly affect electricity demand, leading to seasonal patterns. Seasonality can be understood by the distinct cooling needs trough-out the year. Economic and business activities generate different seasonal patterns on distinct time scales: intra-daily, weekly, and monthly. The electricity demand is higher during the day (at business hours) than at night. Moreover, we expect a lower demand on weekends than during business days. Therefore, the electricity supply/demand is highly dependent on time, e.g., it changes trough both the day and week.

In order to capture seasonality patterns on the spot prices, we start by analyzing the daily spot price in each year. To illustrate the distinct dynamics that spot prices undergo, we display in Figure 7.2 the spot prices in the years 2011 and 2014. A descriptive statistics summary for the whole sample is given in Table 7.2.

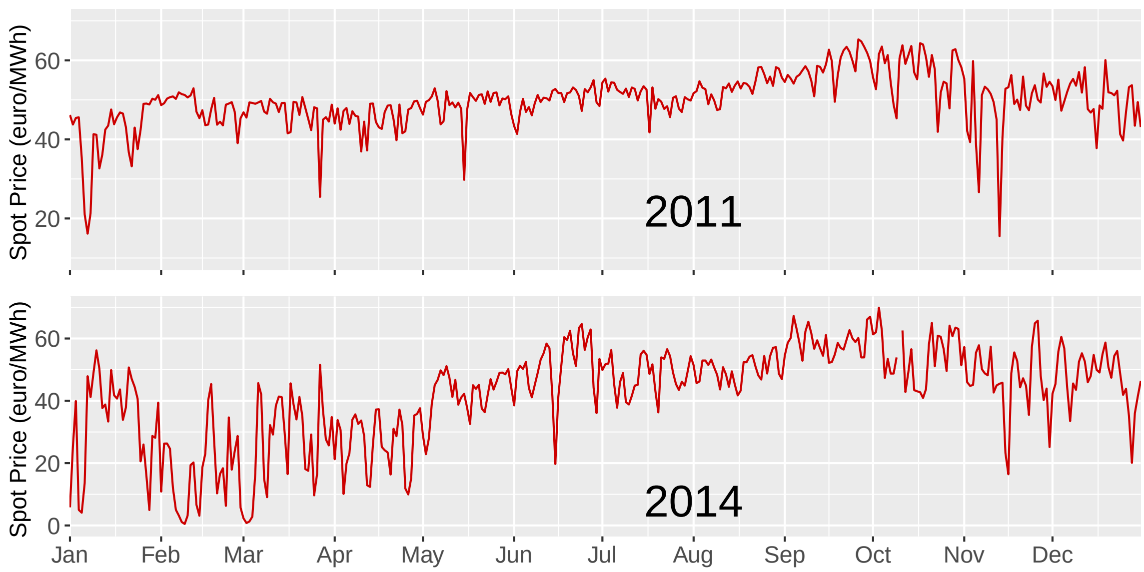

Fig. 7.2 Daily electricity prices (€/MWh) for the following years: 2011, 2012, 2013, 2014, and 2015.

Several conclusions can be extracted from Fig. 7.2 and confirmed in Table 7.2. The volatility of spot prices is highly dependent on the year. In 2011 it was 6.92€/MWh, being lower than in the years 2012-2015. The lowest volatility occurred in 2009 and the highest in 2013, with a value more than three times higher. From a visual inspection of Fig. 7.2, it seems that the volatility is lower on the middle than at both the beginning and ending of each year. We will verify this when we calculate monthly averages.

	2006	**2007**	**2008**	**2009**	**2010**	**2011**
Maximum	91.660	79.210	82.130	58.620	54.910	65.310
Day	01-31	12-17	01-29	01-16	12-11	09-26
Minimum	24.050	22.380	46.300	3.4000	2.4700	15.520
Day	12-08	02-25	12-25	12-31	04-03	11-13
Mean	50.532	39.346	64.426	36.962	37.011	49.922
Std. Dev.	13.601	8.858	7.1905	5.5831	10.633	6.9245
Kurtosis	3.6965	4.9228	2.1997	9.0005	3.7924	7.4789
Skewness	1.0110	1.2423	−0.0690	0.4559	−1.0723	−1.1616

	2012	**2013**	**2014**	**2015**	**2016**
Maximum	67.510	93.110	71.060	66.410	59.650
Day	12-12	12-08	10-10	12-02	10-20
Minimum	9.5500	0.0000	0.4800	16.350	5.4600
Day	11-01	04-01	02-09	02-22	05-08
Mean	47.237	44.257	42.130	50.324	35.318
Std. Dev.	8.8362	17.464	15.657	9.2580	10.912
Kurtosis	5.5484	4.0608	3.1127	3.8368	3.1020
Skewness	−1.3597	−0.4343	−0.8609	−0.8428	−0.5416

Table 7.2 Descriptive statistics for annual spot prices.

The spot price variation in 2013 is remarkable, being zero on 1 April and 93.11 on 8 December (the highest value of the sample). The variation range of both the kurtosis and skewness indicates that the spot price distribution is high dependent on the year. However, this is expected due to the high number of factors that affects electricity prices, some of which are completely unpredictable.

The financial crisis of 2009 affected the prices of several energy commodities: electricity, gas, oil, and coal. All around Europe, the average electricity prices went down in 2009, when compared to 2008. Both the wholesale and retail electricity prices have shown a downward trend. Despite the colder than normal winter temperatures that triggered electricity demand, the industrial sector, influenced by the financial crises, had a crucial impact on the lower electricity demand in 2009.

Looking at Table 7.2, it is clear the effect that economic crisis had on the MIBEL electricity market. For the first time, due to low demand and overflow of renewable energy, the MIBEL registered 74 hours of thermal power sales for free from 28 December 2009 to 15 January 2010 [25]. The average price decreases from 64€/MWh in 2008 to 37€/MWh in 2009. The electricity price reached the lowest value of 3.4€/MWh in 2009.

The electricity prices remained low in 2010, with approximate the same average as in 2009. In fact, the MIBEL experienced one of the lowest electricity prices on the first quarter of 2010 [25].

Also worth mention is the lowest price value of zero and the highest of 93€/MWh reached in 2013. In April 2003, an unprecedented combination of high hydro-based power generation level and lower level of fossil fuel generation, costlier than the renewables or nuclear, took place in Iberia Peninsula. This exceptional combination of power generation sources lead to several days in April with average prices between zero and 10€/MWh [25]. On the other hand, the wind and hydro-based power generation decreased in December 2013. Therefore, the power generation mix was mainly composed of expensive conventional sources, which drove the spot price up to 93€/MWh, the highest value on the sample.

The next step is to determine monthly averages in electricity spot prices, and analyze possible seasonal patterns. By looking at monthly averages, we are removing intra-daily and weekly seasonal patterns. Monthly averages are given by the arithmetic mean of the individual daily spot prices. The result is plotted in Fig. 7.3, and the descriptive statistics is presented in Table 7.3. April has the lowest average price and September the highest. Figure 7.3 (bottom panel) shows an high volatility on the first months that is confirmed by the standard deviation in Table 7.3. The volatility is higher for months between January and April (bottom panel of Fig. 7.3). The skewness and kurtosis fluctuation ranges show that the distribution of spot prices is strongly dependent on the month.

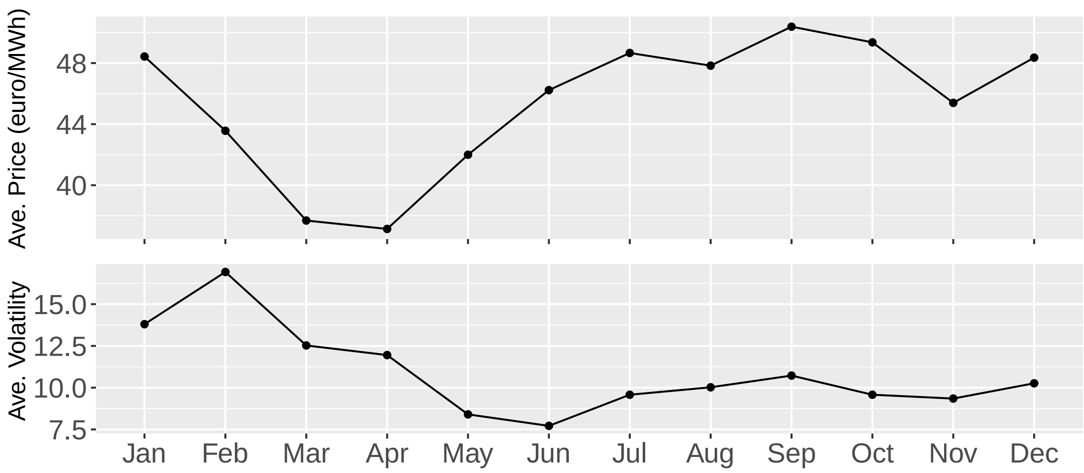

Fig. 7.3 Monthly average spot prices (top) and volatility (bottom).

The average spot price decreases from January to April (Fig. 7.3). Then, in between April and September, the price increases but with a slight decrease in August. October and November show lower values than September, but in December it increases again.

	January	**February**	**March**	**April**	**May**	**June**
Maximum	73.143	72.623	58.997	56.176	56.279	58.336
Year	2006	2006	2008	2008	2008	2008
Minimum	29.057	17.116	19.629	18.166	25.765	36.825
Year	2010	2014	2010	2013	2016	2009
Mean	48.428	43.567	37.687	37.138	41.996	46.228
Std. Dev.	13.800	16.927	12.527	11.951	8.4008	7.7127
Kurtosis	2.4583	2.3242	1.7973	1.8961	2.7214	1.5298
Skewness	0.5153	0.3031	0.1685	−0.0483	−0.2780	0.1456

	July	**August**	**September**	**October**	**November**	**December**
Maximum	68.189	70.101	73.028	69.768	66.532	63.640
Year	2008	2008	2008	2008	2008	2013
Minimum	34.618	34.677	35.805	35.782	32.390	30.434
Year	2009	2009	2007	2009	2009	2009
Mean	48.662	47.832	50.385	49.358	45.395	48.357
Std. Dev.	9.5764	10.021	10.723	9.5770	9.3478	10.261
Kurtosis	2.8070	3.3788	3.0322	3.0118	3.8209	2.2033
Skewness	0.5038	0.7211	0.5286	0.5924	0.9478	−0.2896

Table 7.3 Descriptive statistics of monthly averages spot prices.

To search for patterns connected with the four different seasons, we calculate the average spot price for each one. Table 7.4 shows the obtained values. The highest average price happen in fall and the lowest in spring. The summer has a higher average spot price than winter. Prices are normally higher in summer when total demand is high, requiring more expensive power generation so that supply can meet the increased demand. The demand peaks coincide with the highest (summer) and lowest (winter) temperatures. This relationship between electricity demand and temperature is non-linear, increasing both for decreasing and increasing temperatures [26].

	Fall	**Spring**	**Summer**	**Winter**
Maximum	79.650	72.360	75.860	93.110
Minimum	9.5500	0.0000	18.180	0.4800
Mean	48.443	38.960	47.589	46.853
Std. Dev.	11.495	13.370	10.074	16.788
Kurtosis	2.9008	3.3120	2.7893	3.2470
Skewness	0.2209	−0.6617	0.4205	−0.0008

Table 7.4 Descriptive statistics of seasons average spot prices.

The use of gas-powered equipment for heating, makes the residential consumption of gas heaviest during winter months. Thus, the winter prices are higher compared with lower summer prices. On the other hand, cooling is made via electric air-conditioning, making the electricity demand highest on summer. Therefore, the gas prices show the opposite season pattern compared with electricity prices.

7.2 Futures Market

In Fig. 7.4 are displayed the 1-month ahead (red), the 2-month ahead (blue), the 3-month ahead (green), and the spot (black) prices [1]. Table 7.5 contains their descriptive statistics. From a visual inspection, all three futures series seem to follow a similar pattern, and their fluctuation reflects the spot price movements. This behavior suggests the existence of a comovement between the spot and futures prices.

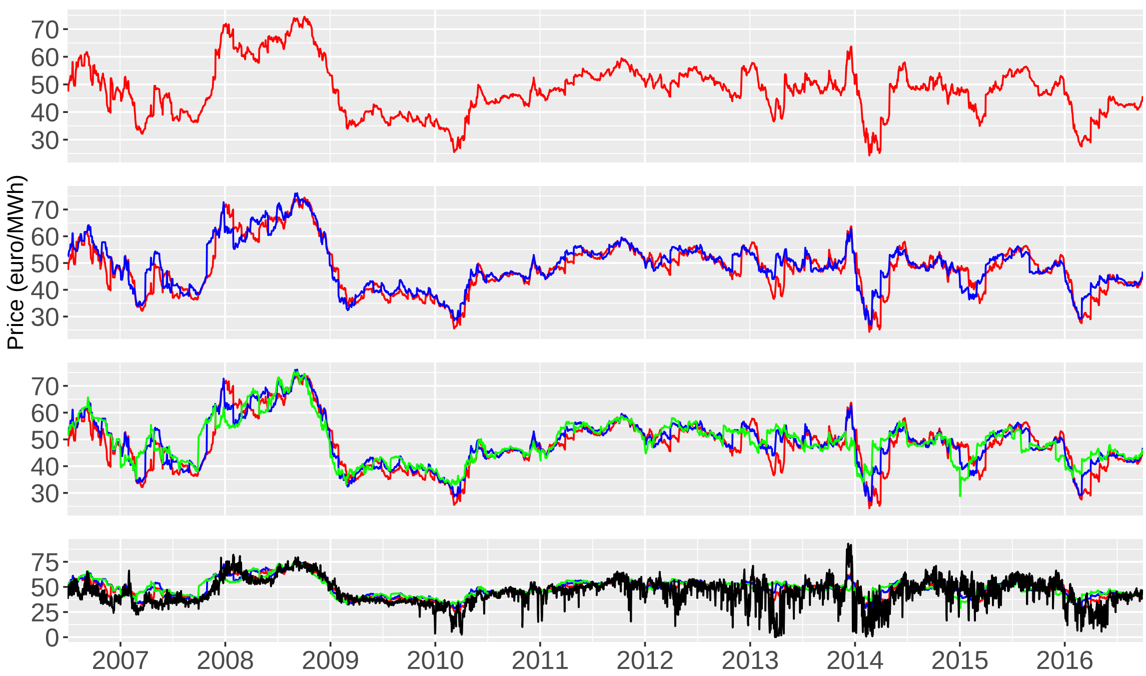

Fig. 7.4 Futures prices for the 1-month ahead (red), the 2-month ahead (blue), and the 3-month ahead (green) contracts. The spot prices (black) are also shown on the bottom panel.

Comparing the descriptive statistics of both futures and spot prices (see Table 7.1), we verify that the spot market is more volatile than the futures market. While the average futures price increases with time do delivery, the volatility decreases. Both the skewness and kurtosis increase with time do delivery, showing that the futures prices distribution becomes more positive asymmetrical and leptokurtic. For all the three futures prices series, the distributional normality is rejected by the Jarque-Bera test.

[1] Their definitions can be seen in Section 6.1.2.

The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) statistical results show that all series are stationary at the 0.1 level.

	1-month ahead	**2-month ahead**	**3-month ahead**
Maximum	74.500	76.130	75.380
Day	2008-10-03	2008-09-08	2008-08-29
Minimum	24.250	26.880	28.750
Day	2014-02-20	2014-02-27	2015-01-02
Mean	47.886	48.838	49.083
Std. Dev.	9.3186	8.8254	7.9898
Kurtosis	3.1938	3.2379	3.5039
Skewness	0.2898	0.3687	0.5624
JB statistic	40.191	64.582	161.20
p-value	0.0000	0.0000	0.0000
ADF statistic	−3.3815	−3.5220	−3.1617
p-value	0.0566	0.0402	0.0945
PP statistic	−23.213	−22.722	−21.311
p-value	0.03707	0.04079	0.05286

Table 7.5 Descriptive statistics for the 1-month ahead, the 2-month ahead (blue), and the 3-month ahead futures prices. The Jarque-Bera (JB) statistic is used to test the normality: being the null hypothesis (H_0) of normality tested against the alternative hypothesis (H_1) of non-normality. Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) statistics are useful to check for the presence of unit roots: both test the null hypothesis (H_0) of presence of an unit root against the alternative hypothesis (H_1) of no unit root.

The cross correlation function for (X_{t+h}, Y_t), where $t = 0 \pm 1 \pm 2 + ...$ represents the days, measures the correlation of both X_{t+h} and Y_t series. In Fig. 7.5 we plot the cross correlation function for (S_{t+h}, F_t). The conclusion one can take from Fig. 7.5 is that F_1 follows the spot more closely, and both F_2 and F_3 are lagged with relation to the spot. In other words, a fluctuation in the spot prices is transmitted firstly to the 1-month ahead futures series, then it diffuses to the 2-month ahead futures, and finally to the 3-month ahead futures. At a specific time, a fluctuation in the spot price market affects the future expectations of the spot evolution, then the futures contracts that first reflect this new information will be the ones with closest maturity.

In the process of forecasting month-ahead spot prices, market agents readjust and accommodate new information arriving from spot prices fluctuations in their expectations. Therefore, it is expected that the correlation between one month-ahead and the spot prices should be higher than two or three month-ahead prices. In fact, the higher correlation values obtained between the spot and the one month-ahead futures prices approve the visual comovement tendency of both series shown in Fig. 7.4.

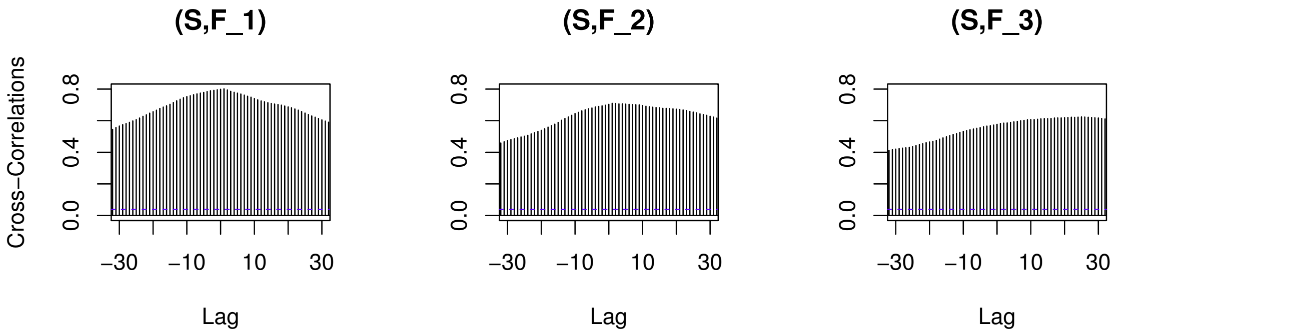

Fig. 7.5 Cross correlation function for (S_{t+h}, F_t^i) , where $t = 0 \pm 1 \pm 2 + ...$ is the lag. F^1, F^2, and F^3 denotes, respectively, the 1-month ahead, the 2-month ahead, and 3-month ahead futures prices.

To understand the dynamics of both futures and spot series, we show their values for 2009 and 2015 in Fig. 7.6. It is clear the higher volatility of the spot prices. While the spot market is a one-day ahead market, the futures market is an 1 to 3 -month ahead (for monthly contracts). The futures prices volatility is much lower than the one that characterizes the spot market, which reflects the daily time dependent supply/demand relationship.

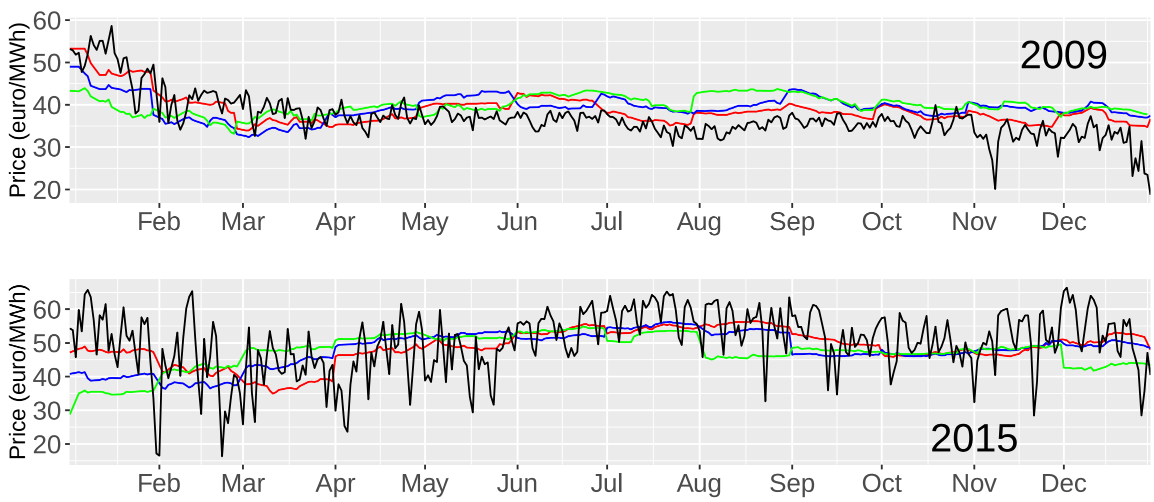

Fig. 7.6 Spot (black) and futures prices for the 1-month ahead (red), the 2-month ahead (blue), and the 3-month ahead (green) contracts in the years 2009 (top) and 2015 (bottom).

7.3 Risk Premium

Herein, we determine and analyze the ex-post risk premium of the SPEL base load futures contracts for monthly delivery. For simplicity, we designate hereafter the ex-post risk premium simple as risk premium. We have introduced the (ex-post) risk premium in Chapter 4.3 as

$$RP_{t,T} = RP_{t,T}^{\text{ex-post}} = F_{t,T} - \bar{S}_T, \tag{7.1}$$

where $F_{t,T}$ stands for the futures price at trading day t with (future) delivery time period T[2], and $\bar{S}_T$ denotes the realized average spot price over the corresponding futures delivery period T. Since the realized spot price $\bar{S}_T$ is a known value, the futures risk premium only depends on its price definition $F_{t,T}$.

The last trading day settlement price[3] is generally used as contract price, which in our notation is represented by $t = 0$. Distinct definitions can be used for the contract price $F_{t,T}$, e.g., the average settlement prices over a specific trading period. Regardless of how $F_{t,T}$ is selected, each contract has an associated risk premium determined by Eq. (7.2).

We calculate the risk premium for the futures contracts using the last trading days settlement prices, $F_{0,T}$, as futures prices,

$$RP_{0,T} = F_{0,T} - \bar{S}_T. \tag{7.2}$$

The result is presented in Fig. 7.7. In the top panel we display both $F_{0,T}$ and $\bar{S}_T$, and in the bottom panel the risk premium. The risk premium fluctuates between positive and negative values. The relation between futures prices and the realized average spot prices depends on the risk aversion among market participants.

[2]The delivery period is the time period following the trading period on which the financial settlement or physical delivery of the electricity is processed.

[3]The last trading day settlement price is the settlement price on the last day on which a certain contract is tradable in the market.

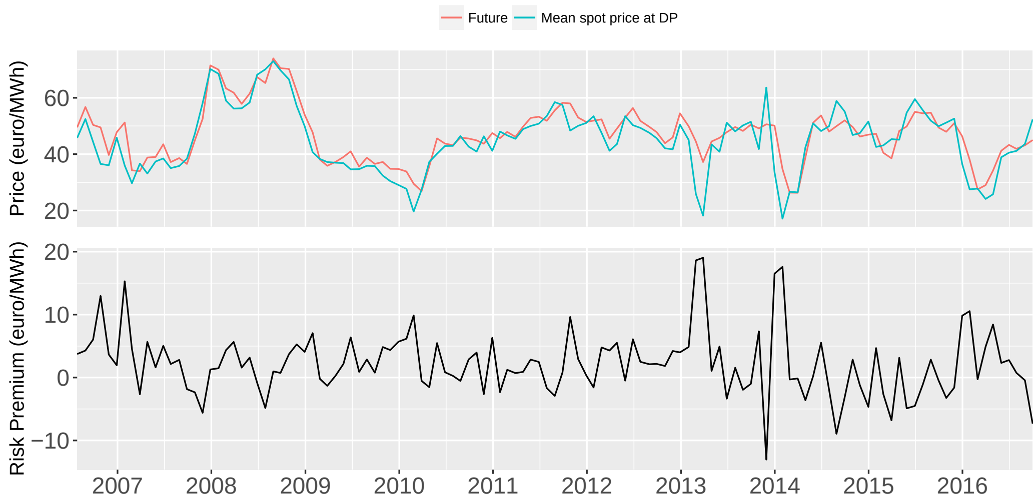

Fig. 7.7 The futures prices on the last trading days, $F_{0,T}$, and the average spot price in the delivery period, $\bar{S}_T$ (top), and the respective risk premium $RP_{0,T}$ (bottom) [Eq. (7.2)] for each contract. The correlation coefficient between $F_{0,T}$ and $\bar{S}_T$ is 0.8928

Sellers with a more risk-averse posture than buyers are willing to accept a lower price for the futures, resulting in an average positive risk premium. Buyers with a more risk-averse attitude than sellers are able to pay a higher price for the futures, and the risk premium becomes negative on average. Accordingly, an electricity generator company can protect its exposure to spot price fluctuations by selling futures contracts on its expected output. On the other hand, an electricity retailer company that wishes to cover its exposure on spot prices buys futures contracts to secure its future electricity needs. Futures are an import mechanism for transferring risk between market agents. The correlation coefficient between $F_{0,T}$ and $\bar{S}_T$ of 0.8928 shows their expected linear relation.

The behavior between futures and spot prices for each contract can be analyzed by writing the risk premium as

$$RP_{0,T}(\%) = \frac{F_{0,T} - \bar{S}_T}{\bar{S}_T}. \tag{7.3}$$

The result of Eq. (7.3) is displayed in Fig 7.8, and a descriptive statistics summary is given in Table 7.6.

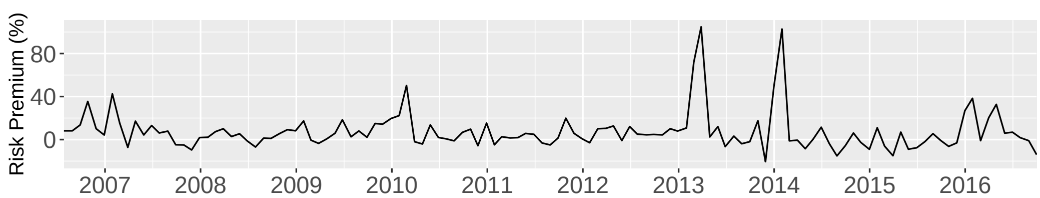

Fig. 7.8 The risk premium (%) for each contract [Eq. (7.3)].

Several conclusions can be drawn: the risk premium is positive with an average value of 7.5352%, the high volatility value 18.094 reflects a broad risk premium distribution, the high kurtosis indicates the frequent occurrence of spikes in the risk premium distribution, and the positive skewness reflects the more frequently occurrence of positive spikes (Fig 7.8). The average positive risk premium indicates that market agents are willing to pay a higher price for futures contracts in order to reduce their risk exposure. The futures contracts were traded on average at 7.5352% above the spot prices.

	Risk Premium (%)
Maximum	104.78
Contract	FTB M Apr-13
Minimum	-20.490
Contract	FTB M Dec-13
Mean	7.5352
Std. Dev.	18.094
Kurtosis	15.505
Skewness	3.0655
ADF statistic	-4.4847
p-value	< 0.0100
PP statistic	-129.40
p-value	< 0.0100

Table 7.6 Descriptive statistics for the risk premium [Eq. (7.3)]. Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) statistics are useful to check for the presence of unit roots: they test the null hypothesis (H_0) of the presence of an unit root against the alternative hypothesis (H_1) of no unit root.

The minimum and maximum risk premium occurred in April 2013 and December 2013, respectively. As we mentioned when we analyzed the spot prices, an unprecedented mix power generation level occurred in April 2003, leading to several days with average spot prices between zero and 10€/MWh. The opposite was reported in December 2013: the power generation mix was mainly composed of expensive conventional sources that drove the spot price up to 93€/MWh. Therefore, the maximum/minimum risk premium values are explained by the inability to forecast these extreme spot movements. The April 2013 contracts were traded at a price 105% higher than the realized average spot prices. On the contrary, the December 2013 contracts were exchanged at a price 20% lower than the the average realized spot prices.

The risk premium may also be studied by delivery period. In Fig. 7.9 we show the risk premium for each month (delivery period) as a function of the year. Monthly average risk premium and the respective standard deviation are plotted in Fig. 7.10. Besides the presence of a high volatility throughout the year, February and April have the highest risk premium volatilities (see bottom panel of Fig. 7.10). The volatility distribution is expected by the occurrence of intense spikes in the risk premium for the first months of the year, particularly in February and April (see Fig. 7.9), where the risk premium reaches values as high as 100%. The risk premium shows an overall oscillating pattern.

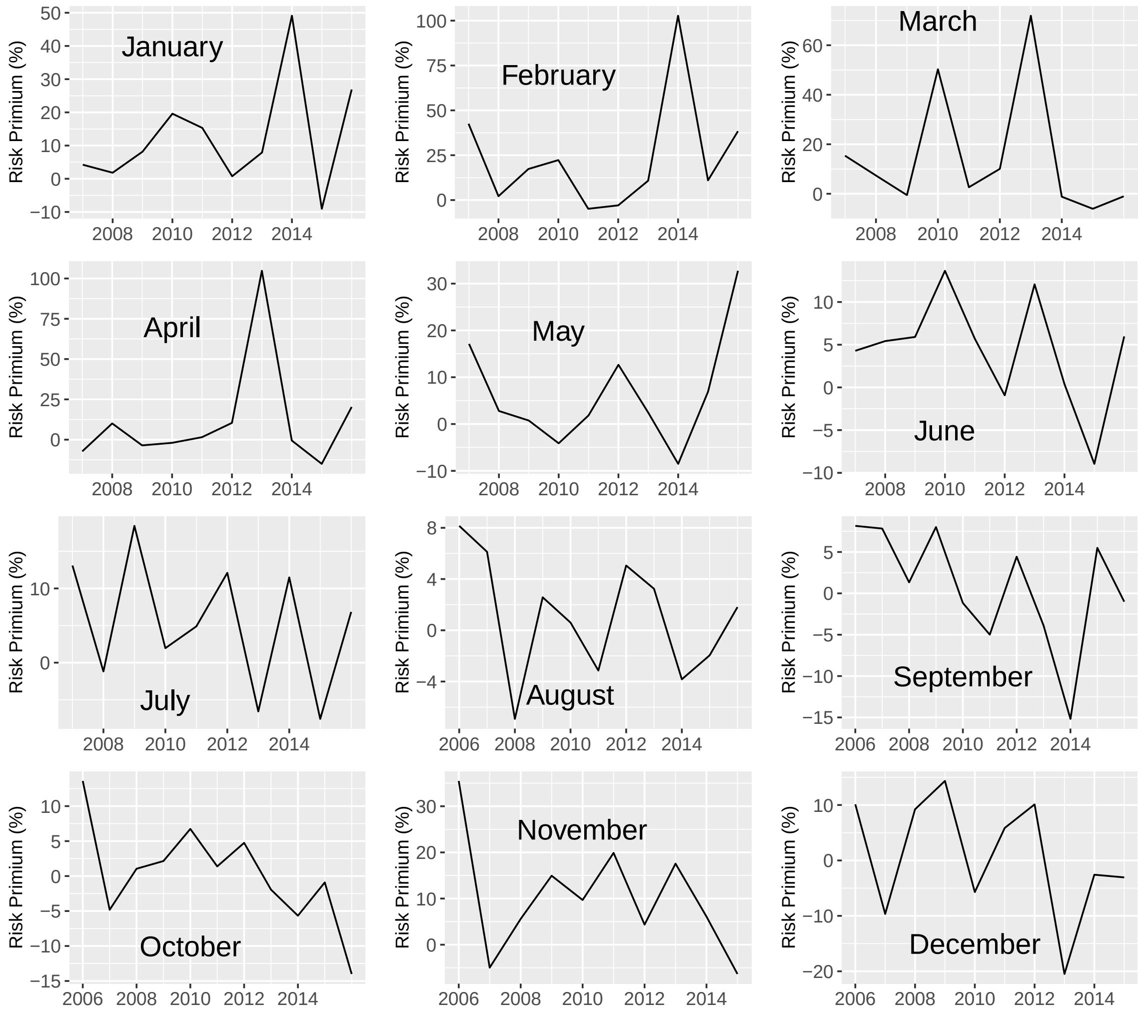

Fig. 7.9 Risk premium by the contracts delivery periods.

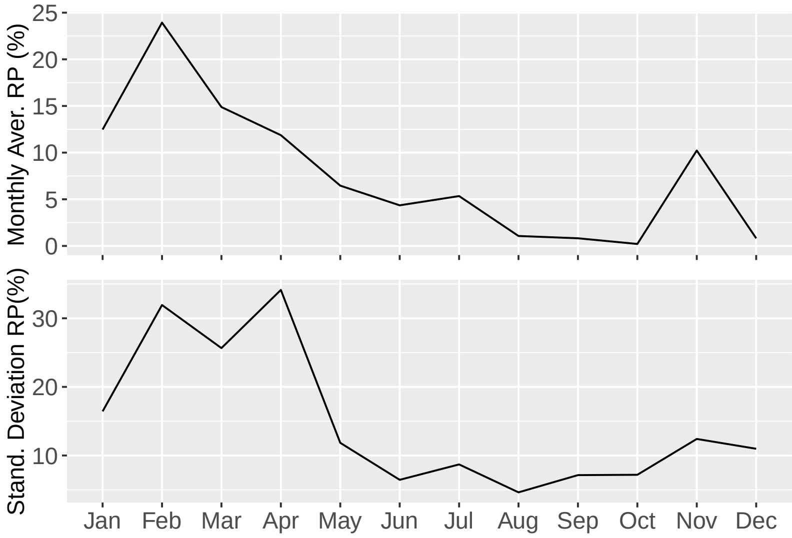

Fig. 7.10 Monthly average risk premium (top) and standard deviation (bottom).

It is also interesting to analyze the risk premium by season. Some statistical information can be seen in Table 7.7. The risk premium and its volatility are higher in winter and lower in summer. The winter futures contracts were traded on average 17.1% higher than the respective realized spot prices. On the other hand, summer futures contracts were traded on average 2.3% higher than the realized spot prices. Furthermore, the lowest risk premium volatility on summer reflects the higher forecast power of futures market players for the summer months spot prices.

	Fall	**Spring**	**Summer**	**Winter**
Maximum (%)	35.483	104.78	18.435	102.74
Minimum (%)	−20.490	−15.017	−15.181	−9.0458
Mean (%)	3.6384	7.5626	2.3188	17.098
Std. Dev.	11.000	20.699	7.0426	25.095
Kurtosis	3.9723	17.541	3.0683	6.0677
Skewness	0.4421	3.5922	−0.0876	1.7825

Table 7.7 Descriptive statistics of the average risk premium by season.

7.3.1 Trading period

The trading period of a contract comprises the time period between the first and the last trading days, during which the futures contracts can be traded. To analyze how the risk premium behaves over the trading period, we synchronize all futures contracts by their last trading days (we follow the procedure applied in [21]). We determine the average risk premium over all contracts as a function of the remaining trading days, i.e., the risk premium at each trading day is averaged over all contracts.

For the contracts synchronization procedure one must assure that only business days are considered. This is simple to obtain since the trading period only covers the trading days, and thus only business days. If we define a variable that gives the remaining number of days until the last trading day of a contract, different results are obtained whether it is considered the total number of days or only the number of trading days (business days). We illustrate this feature in Fig. 7.11, where we plot several January contracts prices as a function of both remaining days and trading days until the last trading day.

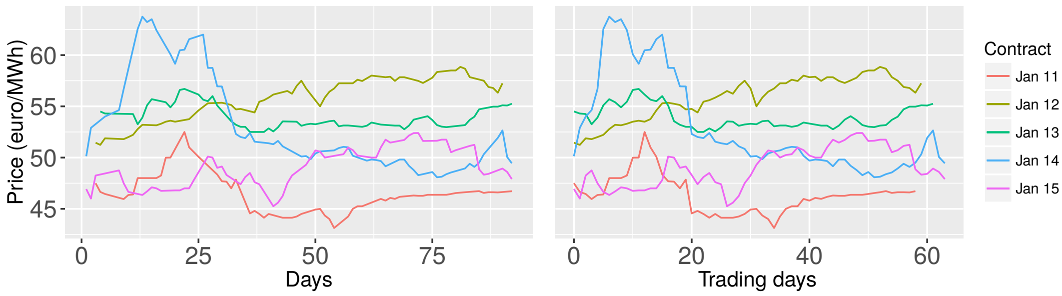

Fig. 7.11 The price of futures contracts with delivery in January 2011-2015 as a function of the days (left) and the trading days (right) up to the last contracts trading days.

Hence, different results are obtained whether the average risk premium over all contracts is performed by the remaining trading days or the by remaining days until the last trading day. The results are shown in Fig. 7.12. The average risk premium to be considered must be the one determined as a function of the remaining trading days (blue line). By looking at Fig. 7.12, we see that the risk premium decreases as we get closer to the last trading day, or, in other words, as the remaining trading days decreases. This means that hedging electricity production near the contract maturity has a lower return than hedging long time prior to contract maturity. On the other hand, hedging electricity needs near the contract maturity has a higher return than hedging long time prior.

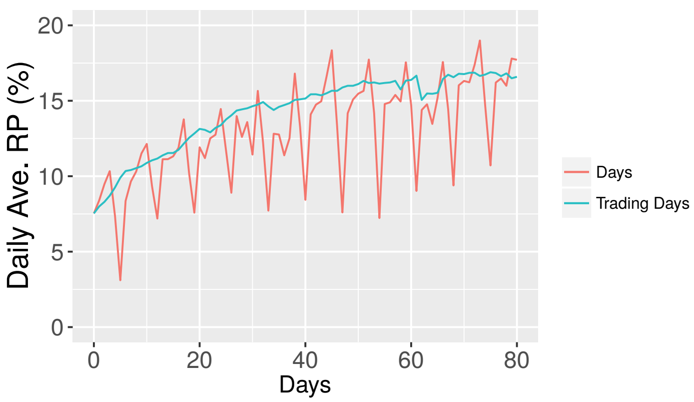

Fig. 7.12 Average risk premium over all contracts as a function of the remaining days (red) and remaining trading days (blue) until the last contract trading day.

When we look at the average risk premium as a function of the remaining trading days in Fig. 7.13, a striking result is seen: a non-linear dependence of the average risk premium is present. Even though it seems to exist an almost linear dependence for the last 7 trading days (center panel in Fig. 7.13), an approximate square root dependence is present when we consider the last 80 trading days: $RP_{t,T} \propto \sqrt{t}$, where t stands for the remaining trading days, with $t = 0$ representing the last trading day. The variation of the risk premium is more intense near the contract maturity. This seems a reasonable feature since the forecast power depends in a non-linear fashion on time to maturity: the information near the maturity is much more reliable for an accurate forecasting of the future spot prices, and thus the risk premium converges quickly to lower values.

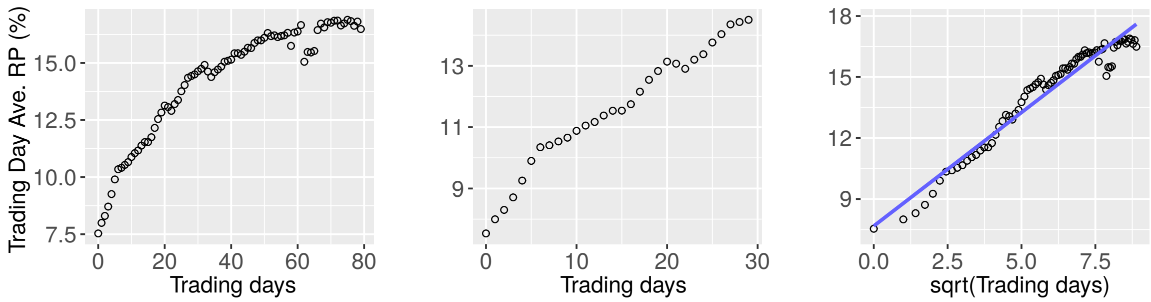

Fig. 7.13 Average risk premium over all contracts as a function of the remaining trading days (left panel) and a zoom for the last 30 trading days (center panel). The linear regression of the left panel data is shown on the right panel.

We perform a linear regression for the risk premium on the the square root of the remaining trading days t,

$$RP_{t,T} = \alpha + \beta\sqrt{t} + \epsilon. \tag{7.4}$$

The regression results are shown in Table 7.8 and in the right panel of Fig. 7.13.

α	*p-value*	β	*p-value*	R^2
7.6711	0.0000	1.1171	0.0000	0.9495

Table 7.8 Results for the linear regression [Eq. (7.4)].

An increasing risk premium with increasing time to the contract maturity was also obtained for the California-Oregon Border area in [21], but with a linear dependence. In [19], for futures contracts traded in the European Energy Exchange (EEX) for delivery in Germany, the same behavior is seen in the region of 60 to 70 days to maturity, but with a subsequently decrease more far for maturity. Its behavior followed a quadratic plus a linear dependence for the risk premium on days to maturity [19].

7.3.2 Dynamics

In the previous Section, we concluded that the risk premium decreases as we approach the last trading day (as the remaining trading days decreases). Herein, the same conclusion is achieved trough a different approach. We calculate the risk premium for each contract by taking as the futures price, $F_{t,T}$, the average settlement prices over: the last 0-30 trading days, $F_{[0,30],T}$; the last 30-60 trading days, $F_{[30,60],T}$; and the last 60-90 trading days, $F_{[60,90],T}$. The results are displayed in Fig. 7.14 and the respective descriptive statistics summary in Table 7.9.

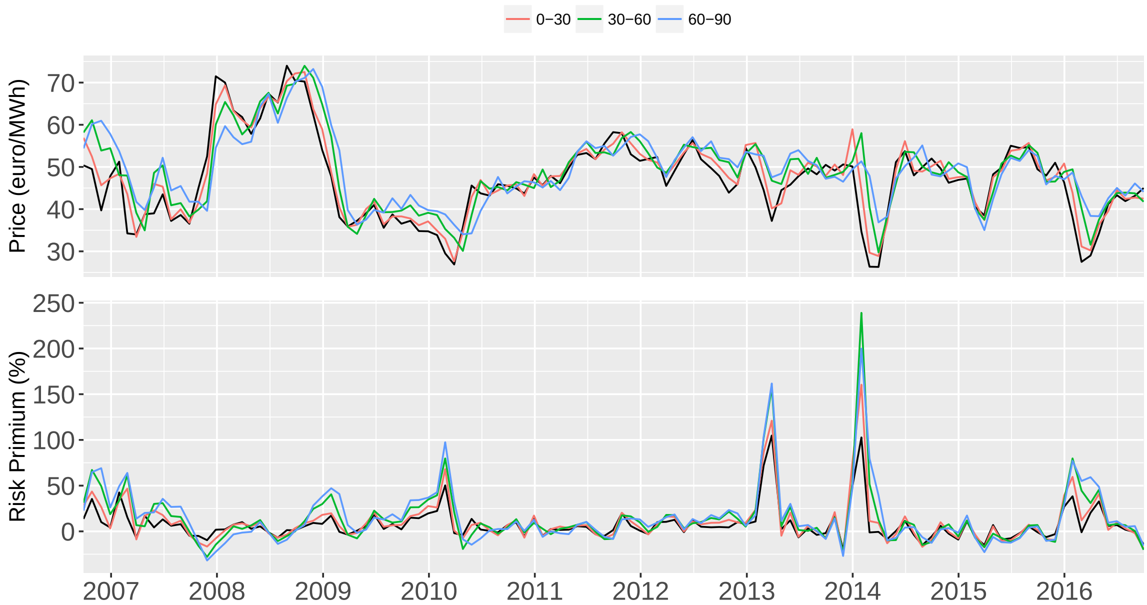

Fig. 7.14 Risk premium (%) (bottom) for every contract by using as contract price (top) the average settlement prices over: the last 0-30 trading days, $F_{[0,30],T}$ (red); the last 30-60 trading days, $F_{[30,60],T}$ (green); the last 60-90 trading days, $F_{[60,90],T}$ (blue); and the last trading day price, $F_{0,T}$.

Several important conclusions can be taken from Fig. 7.14 and Table 7.9. The average risk premium and volatility decrease as we approach the contracts maturity. When the contracts are being traded far from their maturity, the high risk premium and volatility reflect the poor and divergent forecasts made by market agents. As the trading day approximates the last trading day and thus the contract maturity, the available information allows more accurate forecasts, and the forecast discrepancy decreases. This characteristic explains the decrease of both the average risk premium and volatility as the trading period advances towards the contracts maturity.

	RP{$F_{0,T}$}	RP{$F_{[0-30],T}$}	RP{$F_{[30-60],T}$}	RP{$F_{[60-90],T}$}
Maximum (%)	104.78	160.40	238.99	199.92
Minimum (%)	-20.490	-24.466	-27.935	-31.860
Mean (%)	7.5352	10.576	14.348	15.921
Std. Dev.	18.094	24.555	32.462	32.482
Kurtosis	15.505	16.918	23.445	13.495
Skewness	3.0655	3.1652	3.7769	2.6814
ADF statistic	-4.5228	-4.4352	-4.3306	-4.1417
p-value	< 0.0100	< 0.0100	< 0.0100	< 0.0100
PP statistic	-123.18	-122.91	-126.58	-126.55
p-value	< 0.0100	< 0.0100	< 0.0100	< 0.0100

Table 7.9 Risk premium (%) descriptive statistics using as contract price the average settlement prices over: the last 0-30 trading days, $F_{[0,30],T}$; the last 30-60 trading days, $F_{[30,60],T}$; the last 60-90 trading days, $F_{[60,90],T}$; and the last trading day price, $F_{0,T}$. Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) statistics check for the presence of unit roots: both test the null hypothesis (H_0) of presence of an unit root against the alternative hypothesis (H_1) of no unit root.

In Fig. 7.15 we show the risk premium for August contracts. As the last trading day gets closer, the risk premium differs among contracts. To illustrate, let us focus on the 2007 and 2008 August contracts. The average risk premium of the 2008 contract is higher than 25% for the 60-90 trading days (blue line), then it decreases to 15% for the 30-60 trading days (green line), and, finally, the average risk premium of the last 30 trading days (red line) is already very close to the risk premium in the last trading day (black). For the 2008 contract, a similar behavior occurs but with negative values for the risk premium. In both cases, the forecasting accuracy increases as the contract maturity approaches. The positive and negative values for the risk premium show an underestimate and an overestimate of the future spot price in the years 2007 and 2008, respectively.

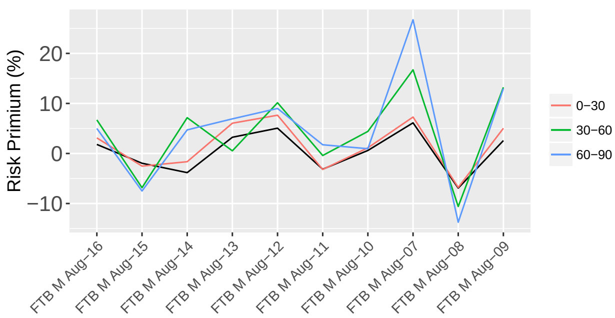

Fig. 7.15 Risk premium for August contracts by using as contract price the average settlement prices over: the last 0-30 trading days, $F_{[0,30],T}$ (red); the last 30-60 trading days, $F_{[30,60],T}$ (green); the last 60-90 trading days, $F_{[60,90],T}$ (blue); and the last trading day price, $F_{0,T}$ (black). T corresponds to August months for the years 2009-2016.

7.3.3 Unbiased Forward Hypothesis

In an efficient market the futures prices are the best predictors of future spot. Therefore, there is no risk premium in efficient markets. Several studies show, however, that the futures prices are not unbiased predictors of future spot due to a time varying risk premium. The presence of risk premium indicates that the market is inefficient. In electricity markets, where consumers and generators can negotiate in both spot and futures markets, these inefficiencies can be explored in designing strategies with risk-less profits.

The weak-form of the Efficient Market Hypothesis implies that asset prices incorporate all available historical information, and that price changes are unpredictable in terms of their own past. In forward markets this means that all available information is incorporated into forward prices. Historical spot price information should not improve predictions of future spot prices when compared to predictions based exclusively on the forward prices. An intuitive way to test the weak-form Efficient Market Hypothesis is via the unbiased forward hypothesis, which states that futures prices are unbiased forecasts of future spot prices, i.e.,

$$\bar{S}_T = \alpha + \beta F_{t,T} + \epsilon_T, \tag{7.5}$$

if $\alpha = 0$ and $\beta = 1$. The residuals ϵ_T must have zero mean and being non-correlated. As in [27], we assumed that an α significantly different from zero indicates the presence of systematic risk premium, and β significantly different from one shows evidence of biased predictions, and thus of a forecast error.

We are going to analyze the linear regression, Eq. (7.5), using several definitions for the futures contract price, $F_{t,T}$. Let us denote the remaining trading days by $t = 0, 1, 2, \ldots$. As before, $F_{0,T}$ is the contract price on the last trading day (the last settlement price). We define $F_{[t_1,t_2],T}$ as the average settlement prices between the trading days t_1 and t_2, and $F_{\text{all},T}$ is the average settlement prices over the whole trading period.

We start by fixing $t_1 = 0$, i.e., $F_{[0,t_2],T}$, and increase t_2 in order to compare the regression results with the ones obtained for $F_{0,T}$. Table 7.10 summarizes the results. To take non-spurious conclusions from the regression analysis, both series must be stationary. Otherwise, misleading results could be obtained due to spurious regression. From the ADF and the PP unit root tests, we reject the null hypothesis of non-stationary for all series. Even though the residuals show no correlations, the residuals squared for $F_{[0,5],T}$, $F_{[0,10],T}$, and $F_{[0,15],T}$ seam to contain some correlations. Then, we perform a robust linear regression using the Newey–West estimator, which uses heteroskedasticity and auto-correlation consistent covariance matrix estimators.

From Table 7.10 we see that as we increase the time window, on which the price average is performed, the α becomes statistically zero. α is statistically different from zero at 0.1 level only for both $F_{0,T}$ and $F_{[0,5],T}$. Therefore, unless we use as contract price the last trading day or the last five trading days average, there is no evidence for systematic risk using averages over longer trading periods. Furthermore, β is always significant and its value increases as we approach the last trading day. When we take $F_{\text{all},T}$, the estimated value $\beta = 0.94981$ indicates that the forecasts made by market agents underestimated the spot prices. On the other hand, we obtain $\beta = 1.04164$ for $F_{0,T}$ that signs an overestimation of the spot prices. The best predictor of spot prices is $F_{[0,10],T}$, because the systematic risk is statistical zero and β is almost one.

	$\mathbf{F_{0,T}}$	$\mathbf{F_{[0,5],T}}$	$\mathbf{F_{[0,10],T}}$	$\mathbf{F_{[0,15],T}}$	$\mathbf{F_{all,T}}$
$\boldsymbol{\alpha}$	-4.1705	-3.7762	-2.6531	-2.0225	-1.6372
p-values	0.0195	0.0581	0.2442	0.4055	0.6431
$\boldsymbol{\beta}$	1.0416	1.0264	0.9973	0.9810	0.9498
p-value $(H_0 : \beta = 0)$	< 0.0000	< 0.0000	< 0.0000	< 0.0000	< 0.0000
p-value $(H_0 : \beta = 1)$	0.2348	0.5035	0.9526	0.6978	0.4728
$\boldsymbol{R^2}$	0.7971	0.7446	0.6906	0.6558	0.4694
$\boldsymbol{Q(10)}$	7.7012	9.3203	10.891	11.527	21.665
p-value	0.6580	0.5020	0.3660	0.3179	0.0169
$\boldsymbol{Q^2(10)}$	9.9179	18.401	23.846	26.076	13.420
p-value	0.4477	0.0486	0.0080	0.0036	0.2012
DW	2.0297	2.0076	2.0340	2.0328	2.1410
p-value	0.5696	0.5210	0.5794	0.5773	0.7875
ADF	-3.2061	-3.2299	-3.1809	-3.2366	-2.9878
p-value	0.0197	0.0184	0.0212	0.0180	0.0361
PP	-143.65	-144.72	-146.37	-148.46	-140.76
p-value	< 0.0100	< 0.0100	< 0.0100	< 0.0100	< 0.0100
KPSS	0.3034	0.3145	0.3016	0.2902	0.2440
p-value	> 0.1000	> 0.1000	> 0.1000	> 0.1000	> 0.1000

Table 7.10 Summary statistics of the robust linear regression of Eq. 7.5, using Newey–West estimators, i.e., heteroskedasticity and autocorrelation consistent covariance matrix estimators. Null hypothesis: $\alpha = 0$ and $\beta = 0$ **[**$\alpha = 0$ and $\beta = 1$**]**. The Ljung-Box statistics $Q(10)$ (we used 10 lag autocorrelation coefficients) and the Durbin-Watson (DW) test the null hypothesis of no residual autocorrelation. $Q^2(10)$ is the Ljung-Box statistics applied to the residuals squared. We applied the Augmented Dickey-Fuller (ADF), the Phillips-Perron (PP), and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests to each $F_{i,T}$ series. In both ADF and PP tests the the null hypothesis (H_0) is the of presence of an unit root, and the alternative hypothesis (H_1) is the absence of an unit root. In the KPSS test the null hypothesis (H_0) is level stationary. The $F_{i,T}$ series are defined as follows: F_0 is contract price on the last trading day, $F_{[t_1,t_2],T}$ is the average contract price between the trading days t_1 and t_2, and $F_{\text{all},T}$ is the average price over the whole trading period.

A similar analysis can be implement by defining $F = F_{[t_1,t_2],T}$, where $[t_1, t_2]$ takes the following values: $[1, 5]$, $[5, 11]$, $[12, 17]$, and $[18, 23]$. This way we have a rolling window with fixed time length of $t_2 - t_1 = 5$ trading days. The contract price is defined as the average price over the trading days enclosed by the window. The results are presented in Table 7.11. As before, a similar behavior is seen: as the window gets near the last trading day (one approaches the contract maturity), β takes higher values and the α becomes statistical significant.

	$\mathbf{F_{0,T}}$	$\mathbf{F_{[1-5],T}}$	$\mathbf{F_{[6-11],T}}$	$\mathbf{F_{[12-17],T}}$	$\mathbf{F_{[18-23],T}}$
$\boldsymbol{\alpha}$	-4.1705	-3.4866	-0.1349	1.0807	1.0598
p-value	0.0195	0.0912	0.9598	0.7002	0.7127
$\boldsymbol{\beta}$	1.0416	1.0189	0.9381	0.9079	0.9009
p-value	< 0.0000	< 0.0000	< 0.0000	< 0.0000	< 0.0000
$\boldsymbol{R^2}$	0.7971	0.7310	0.6073	0.5581	0.5268

Table 7.11 Summary statistics of the robust linear regression of [Eq. 7.5], using Newey–West estimators, i.e., heteroskedasticity and autocorrelation consistent covariance matrix estimators. Null hypothesis: $\alpha = 0$ and $\beta = 0$. $F_{0,T}$ is contract price on the last trading day, $F_{[t_1,t_2],T}$ is the average contract price between the trading days t_1 and t_2.

The main impression is that β is not statistically different from one for all definitions of the futures contract price. Thought not statistically different from one, its estimated value increases as we approximate the last trading day price $F_{0,T}$. An underestimate ($\beta < 1$) is present when the whole trading period is considered, but for the last settlement price an overestimate ($\beta > 1$) occurs. The significance of α also increases when we approach the contract last trading day. When the futures contracts price is $F_{[0,10],T}$, i.e., an average over the last 10 trading days, the estimated parameters are very close to the null hypothesis $\alpha = 0$ and $\beta = 1$.

7.3.4 Predictability

As already mentioned, the weak-form of the Efficient Market Hypothesis suggests that asset prices incorporate all the available historical information, and that price changes are unpredictable in terms of their own past. Therefore, it must be impossible to predict ex-ante the future asset prices. Within the present context, it translates into the impossibility of predicting the risk premium using all the available historical information.

Thus, in this section we analyze whether the spot and futures prices contain some information on the realized risk premium.

I) Futures base

Let us first examine if the futures base, at a specific day to maturity, contains information about the risk premium. The futures base is given by

$$B_{t,T} = \log(F_{t,T}) - \log(S_t) = \log\left(\frac{F_{t,T}}{S_t}\right),$$

where $F_{t,T}$ and S_t are the futures and the spot prices, respectively. The index t represents the remaining trading days, i.e., the number of trading days until the last contract trading day. We want to investigate if the basis has an explanatory power on the realized risk premium. Therefore, we consider the following linear regression

$$RP^{\log}_{0,T} = \alpha + \beta B_{t,T} + \epsilon_T, \tag{7.6}$$

where

$$RP^{\log}_{0,T} = \log(F_{0,T}) - \log(\bar{S}_T) = \log\left(\frac{F_{0,T}}{\bar{S}_T}\right). \tag{7.7}$$

$F_{0,T}$ indicates that the contract risk premium is determined using the last trading day price. The regression results for each $t = 1, 2, ..., 10$ remaining trading days are in Table 7.12.

	α	p-value	β	p-value	R^2	$Q(10)$	p-value	Freq (sign)
$B_{1,T}$	0.0507	0.0000	0.2876	0.0000	0.1429	5.5073	0.8548	0.5854
$B_{2,T}$	0.0485	0.0003	0.2493	0.0000	0.1402	4.4351	0.9256	0.6179
$B_{3,T}$	0.0383	0.0002	0.2478	0.0000	0.2895	6.6021	0.7624	0.6504
$B_{4,T}$	0.0451	0.0000	0.3175	0.0001	0.1932	5.7289	0.8375	0.7154
$B_{5,T}$	0.0589	0.0000	0.2017	0.0046	0.0281	5.3783	0.8645	0.6748
$B_{6,T}$	0.0608	0.0001	0.0295	0.6467	0.0013	6.7836	0.7457	0.5854
$B_{7,T}$	0.0625	0.0000	-0.0248	0.3840	0.0031	8.1313	0.6160	0.6016
$B_{8,T}$	0.0587	0.0000	0.1295	0.4201	0.0265	7.1669	0.7096	0.6016
$B_{9,T}$	0.0607	0.0000	0.0674	0.4781	0.0038	7.1557	0.7107	0.6344
$B_{10,T}$	0.0601	0.0000	0.0220	0.7702	0.0017	7.1154	0.7145	0.6098

Table 7.12 Summary statistics of the robust linear regression [Eq. (7.6)], using Newey–West estimators, i.e., heteroskedasticity and autocorrelation consistent covariance matrix estimators. Freq (sign) is the ratio of the number of times that the signs of $B_{t,T}$ and $RP^{\log}_{0,T}$ match. The Ljung-Box statistics $Q(10)$ test the null hypothesis of no residual autocorrelation.

The main conclusion is that the statistical significance of the futures base explanatory power on the risk premium increases as t approximates the last trading day. Despite the increasing R^2 values (measuring the amount of risk premium variation explained by the basis) near the last trading day, their low values indicates that the futures base do not contain much information on the realized risk premium.

II) Spot Return

Let us now analyze a possible relation between the risk premium and the return of spot prices. We consider the following regression equation,

$$RP^{\log}_{0,T} = \alpha + \beta \Delta S_{[t_1,t_2],T} + \epsilon_T, \tag{7.8}$$

where

$$\Delta S_{[t_1,t_2],T} = \log\left(\frac{S_{t_2}}{S_{t_1}}\right) \tag{7.9}$$

is the spot return over the period $[t_1, t_2]$. Equation 7.8 relates the risk premium of a contract, $RP^{\log}_{0,T}$, with the spot return over a specific time period $[t_1, t_2]$, denoted by $\Delta S_{[t_1,t_2],T}$.

Table 7.13 shows the regression results by considering $\Delta S_{[t,t+1],T}$ with $t = 1, 2, ..., 10.$, which identifies the remaining trading days. The results for the case $\Delta S_{[1,t],T}$ are presented in Table 7.14.

	α	p-value	β	p-value	R^2	$Q(10)$	p-value	Freq (sign)
$\Delta S_{[1,2],T}$	0.0611	< 0.0000	0.0412	0.7002	0.0023	6.9930	0.7261	0.5040
$\Delta S_{[2,3],T}$	0.0541	< 0.0000	0.1949	0.0386	0.1150	11.559	0.3156	0.5690
$\Delta S_{[3,4],T}$	0.0528	< 0.0000	-0.1906	0.0261	0.1143	5.0720	0.8863	0.4800
$\Delta S_{[4,5],T}$	0.0512	< 0.0000	-0.2469	0.0062	0.1347	8.7398	0.5570	0.4800
$\Delta S_{[5,6],T}$	0.0634	< 0.0000	-0.2085	0.0708	0.0279	8.8131	0.5499	0.4230
$\Delta S_{[6,7],T}$	0.0620	< 0.0000	-0.0395	0.2428	0.0069	7.8697	0.6416	0.4720
$\Delta S_{[7,8],T}$	0.0626	< 0.0000	0.0640	0.3727	0.0208	9.3690	0.4975	0.5040
$\Delta S_{[8,9],T}$	0.0601	< 0.0000	-0.1368	0.5398	0.0217	7.3863	0.6885	0.5770
$\Delta S_{[9,10],T}$	0.0615	< 0.0000	0.0017	0.9825	0.0000	7.2832	0.6985	0.5040
$\Delta S_{[10,11],T}$	0.0646	< 0.0000	0.3590	0.0034	0.1387	7.0728	0.7186	0.5690

Table 7.13 Summary statistics of the robust linear regression [Eq. 7.8], using Newey–West estimators, i.e., heteroskedasticity and autocorrelation consistent covariance matrix estimators. Freq (sign) is the ratio of the number of times that the signs of $\Delta S_{[t_1,t_2],T}$ and $RP^{\log}_{0,T}$ match. The Ljung-Box statistics $Q(10)$ test the null hypothesis of no residual autocorrelation.

The first conclusion from Table 7.13 is that $\Delta S_{[4,5],T}$ and $\Delta S_{[10,11],T}$ show the highest significance. Freq (sign) is the ratio of the number of times that the signs of $\Delta S_{[t_1,t_2],T}$ and $RP^{\log}_{0,T}$ match. As expected, their values are likely to fluctuate around 50% due to randomness. Tables 7.13 and 7.14 show that the significance of β also increases in the last trading days.

	α	p-value	β	p-value	R^2	$Q(10)$	p-value	Freq (sign)
$\Delta S_{[1,3],T}$	0.0538	< 0.0000	0.1543	0.0496	0.0998	9.7768	0.4603	0.5450
$\Delta S_{[1,4],T}$	0.0615	< 0.0000	0.0191	0.7779	0.0009	7.6795	0.6601	0.5530
$\Delta S_{[1,5],T}$	0.0530	< 0.0000	-0.2292	0.0002	0.1143	5.2970	0.8705	0.5280
$\Delta S_{[1,6],T}$	0.0544	< 0.0000	-0.2484	0.0011	0.1571	7.3955	0.6877	0.4880
$\Delta S_{[1,7],T}$	0.0590	< 0.0000	-0.1558	0.0885	0.1258	8.0210	0.6268	0.5280
$\Delta S_{[1,8],T}$	0.0544	< 0.0000	-0.2170	0.0248	0.1046	4.4126	0.9268	0.5040
$\Delta S_{[1,9],T}$	0.0502	< 0.0000	-0.2639	< 0.0000	0.1690	4.0597	0.9446	0.5200
$\Delta S_{[1,10],T}$	0.0628	< 0.0000	-0.1364	0.0131	0.0863	5.5589	0.8509	0.4550

Table 7.14 Summary statistics of the robust linear regression [Eq. 7.8], using Newey–West estimators, i.e., heteroskedasticity and autocorrelation consistent covariance matrix estimators. Freq (sign) is the ratio of the number of times that the signs of $\Delta S_{[t_1,t_2],T}$ and $RP^{\log}_{0,T}$ match. The Ljung-Box statistics $Q(10)$ test the null hypothesis of no residual autocorrelation.

III) Future Return

As a last step, we analyze a possible relation between futures prices return and the realized risk premium. As for the spot return, we analyze a possible linear relation between the risk premium and the return of futures contracts. We consider the following regression equation,

$$RP^{\log}_{0,T} = \alpha + \beta \Delta F_{[t_1,t_2],T} + \epsilon_T, \tag{7.10}$$

where

$$\Delta F_{[t_1,t_2],T} = \log\left(\frac{F_{t_2,T}}{F_{t_1,T}}\right) \tag{7.11}$$

is the futures contract return over the trading period $[t_1, t_2]$. The above linear equation relates the risk premium of a contract, $RP^{\log}_{0,T}$, with the futures return in a specific trading time period $[t_1, t_2]$, $\Delta F_{[t_1,t_2],T}$.

The results are presented in Tables 7.15 and 7.16. We see that the statistical significance of α is always realized, and for β increases as we move towards the last trading day. It means that the explanatory power of the regressor $\Delta F_{[t_1,t_2],T}$ is more significant near the contract maturity. When we compare these results with the ones obtained for the futures base and spot returns, a main difference is noticeable in the R^2 regression values. The model explains almost 30% of the variation risk premium for both $\Delta F_{[1,6],T}$ and $\Delta F_{[1,7],T}$ (Table 7.16).

Two striking results are present in Tables 7.15 and 7.16: the signs of the estimated β values and the magnitude of R_{sign}. The β values are always negative, meaning that whatever the period on which the futures return is computed, as long as we are nearer the maturity, the risk premium has a negative dependence on the futures return. If the futures return increases the risk premium decreases, or the other way around.

Furthermore, it is remarkable the low values that R_{sign} continuously takes. From Table 7.16, the R_{sign} values are repeatedly of the order of %30, i.e, the signs of $\Delta F_{[t_1,t_2],T}$ and $RP^{\log}_{0,T}$ only match %30 of the times. In other words, $\Delta F_{[t_1,t_2],T}$ (calculated near maturity) and $RP^{\log}_{0,T}$ show opposite signs %70 of the times. These two features indicate that futures returns near maturity contain information on the realized risk premium.

	α	p-value	β	p-value	R^2	$Q(10)$	p-value	Freq (sign)
$\Delta F_{[1,2],T}$	0.0601	< 0.0000	-0.5947	0.2887	0.0055	6.6488	0.7581	0.3500
$\Delta F_{[2,3],T}$	0.0577	< 0.0000	-1.2131	0.2226	0.0188	6.2562	0.7933	0.4150
$\Delta F_{[3,4],T}$	0.0508	< 0.0000	-2.8023	0.0001	0.1129	8.4238	0.5875	0.3330
$\Delta F_{[4,5],T}$	0.0521	< 0.0001	-2.7992	0.0026	0.2131	4.5747	0.9177	0.3170
$\Delta F_{[5,6],T}$	0.0558	< 0.0000	-2.0005	0.0088	0.0748	7.7339	0.6548	0.3580
$\Delta F_{[6,7],T}$	0.0614	< 0.0000	-0.5008	0.2572	0.0037	7.3218	0.6948	0.4720
$\Delta F_{[7,8],T}$	0.0613	< 0.0000	-0.2768	0.7367	0.0011	7.3847	0.6887	0.4720
$\Delta F_{[8,9],T}$	0.0612	< 0.0000	-0.5800	0.4288	0.0058	7.8531	0.6432	0.4390
$\Delta F_{[9,10],T}$	0.0606	< 0.0000	-0.8048	0.1982	0.0133	7.8235	0.6461	0.5040
$\Delta F_{[10,11],T}$	0.0603	< 0.0000	-2.1435	0.0269	0.0507	11.545	0.3167	0.4550

Table 7.15 Summary statistics of the robust linear regression [Eq. 7.10], using Newey–West estimators, i.e., heteroskedasticity and autocorrelation consistent covariance matrix estimators. Freq (sign) is the ratio of the number of times that the signs of $\Delta F_{[t_1,t_2],T}$ and $RP^{\log}_{0,T}$ match. The Ljung-Box statistics $Q(10)$ test the null hypothesis of no residual autocorrelation.

	α	p-value	β	p-value	R^2	$Q(10)$	p-value	Freq (sign)
$\Delta F_{[1,3],T}$	0.0576	0.0000	-0.7027	0.1070	0.0174	5.9439	0.8200	0.3740
$\Delta F_{[1,4],T}$	0.0506	0.0000	-1.1520	< 0.0004	0.0749	5.4723	0.8575	0.3330
$\Delta F_{[1,5],T}$	0.0404	0.0000	-1.6454	< 0.0000	0.2322	2.7643	0.9864	0.2850
$\Delta F_{[1,6],T}$	0.0360	0.0004	-1.6226	< 0.0000	0.2897	2.4814	0.9911	0.2930
$\Delta F_{[1,7],T}$	0.0379	0.0003	-1.4718	< 0.0000	0.2735	3.1241	0.9783	0.2850
$\Delta F_{[1,8],T}$	0.0382	0.0002	-1.3770	< 0.0000	0.2614	2.6581	0.9884	0.2930
$\Delta F_{[1,9],T}$	0.0390	0.0002	-1.2793	< 0.0000	0.2556	4.7629	0.9064	0.3010
$\Delta F_{[1,10],T}$	0.0421	0.0000	-1.0400	< 0.0000	0.2249	6.8523	0.7393	0.3090

Table 7.16 Summary statistics of the robust linear regression [Eq. 7.10], using Newey–West estimators, i.e., heteroskedasticity and autocorrelation consistent covariance matrix estimators. Freq (sign) is the ratio of the number of times that the signs of $\Delta F_{[t_1,t_2],T}$ and $RP^{\log}_{0,T}$ match. The Ljung-Box statistics $Q(10)$ test the null hypothesis of no residual autocorrelation.

Chapter 8

Conclusion

This work provided an empirical analysis of electricity spot and futures markets of the Iberian Electrical Energy Market, and on the forward risk premium.

The constructed data-set covers the period from 1 March 2006 to 30 September 2016. The monthly contracts are the most liquid contracts in the Iberian futures electricity market. In this work we focused on monthly base (covers all daily hours) contracts, and our data-set incorporates 123 contracts. We analyzed the liquidity of monthly futures contracts, showing that the average of both the number of trades and the volume traded increases gradually as the contracts approximate their last trading day. We constructed three times series for the one-month ahead, two-month ahead, and three-month ahead futures prices.

We examined the dynamics of both the spot and futures prices. We found the presence of high volatility clustering and the occurrence of spikes on the spot prices. These features are mainly attributed to the non-storable property of electricity, and thus to the required perfect equilibrium of supply and demand at every time. Seasonal patters were found in spot dynamics at different time scales. The average spot price was higher in summer and lower in spring.

We found evidences of a collective movement between the spot and the futures prices. A fluctuation in the spot prices is transmitted firstly to the futures contracts close to maturity. The futures prices volatility is lower than the spot prices volatility, reflecting the daily time dependent supply/demand relationship in spot market.

We determined the ex-post risk premium and show that it fluctuates between positive and negative values. The risk premium turned out to be 7.53% on average. Therefore, the futures contracts were traded on average at a value 7.53% higher than the realized spot prices. We studied the month and season risk premium distribution, concluding that the volatility is higher in winter and lower in summer. The winter futures contracts were traded on average 17.1% higher than the respective spot prices. We found that the risk premium exhibits a square root dependence on the trading days to maturity, showing an intense variation to lower values as the contract maturity approaches.

We tested the unbiased forward hypothesis, showing that there is no statistical indication of biased predictions when the futures prices far from maturity are used. On the other hand, when the contract maturity gets closer, there is statistical indications for rejecting the unbiased forward hypothesis .

Finally, we look for explanatory power of the futures base, spot return, and futures return on the realized risk premium. Though we found no statistical indication of explanatory power for the futures base and spot return cases, a statistical significance was observed for the futures return near maturity. The risk premium has a negative dependence on the futures return, as long as we are nearer the maturity. Furthermore, it was remarkable that futures returns and risk premium turned out to have opposite signs %70 of the times. These two features indicate that futures return near maturity contains information about the risk premium.

As a future work, we would like to determine the hedge ratio, i.e., the ratio of the position that one should take in futures contracts that will exactly cancel out the exposure in the spot market.

References

[1] C. Harris. *Electricity Markets: Pricing, Structures and Economics*. The Wiley Finance Series. Wiley, 2011.

[2] A. Eydeland and K. Wolyniec. *Energy and Power Risk Management: New Developments in Modeling, Pricing, and Hedging*. Wiley Finance. Wiley, 2003.

[3] L.C. Hunt and J. Evans. *International Handbook on the Economics of Energy*. Elgar Original Reference Series. Edward Elgar, 2011.

[4] MIBEL website. http://www.mibel.com.

[5] OMIP website. http://www.omip.pt.

[6] Álvaro Capitán Herráiz and Carlos Rodríguez Monroy. Analysis of the efficiency of the Iberian power futures market. *Energy Policy*, 37(9):3566–3579, 2009.

[7] Nicholas Kaldor. Speculation and economic stability. *The Review of Economic Studies*, 7(1):1–27, 1939.

[8] John Maynard Keynes. A treatise on money, 1930.

[9] Alvaro Cartea and Pablo Villaplana. An analysis of the main determinants of electricity forward prices and forward risk premia. In *Quantitative Energy Finance*, pages 215–236. Springer, 2014.

[10] Hendrik Bessembinder and Michael L Lemmon. Equilibrium pricing and optimal hedging in electricity forward markets. *the Journal of Finance*, 57(3):1347–1382, 2002.

[11] Alvaro Cartea and Marcelo G Figueroa. Pricing in electricity markets: a mean reverting jump diffusion model with seasonality. *Applied Mathematical Finance*, 12(4):313–335, 2005.

[12] Álvaro Cartea and Pablo Villaplana. Spot price modeling and the valuation of electricity forward contracts: The role of demand and capacity. *Journal of Banking & Finance*, 32(12):2502–2519, 2008.

[13] Craig Pirrong and Martin Jermakyan. The price of power: The valuation of power and weather derivatives. *Journal of Banking & Finance*, 32(12):2520–2529, 2008.

[14] Fred Espen Benth, Álvaro Cartea, and Rüdiger Kiesel. Pricing forward contracts in power markets by the certainty equivalence principle: explaining the sign of the market risk premium. *Journal of Banking & Finance*, 32(10):2006–2021, 2008.

[15] Dolores Furió and Vicente Meneu. Expectations and forward risk premium in the Spanish deregulated power market. *Energy Policy*, 38(2):784–793, 2010.

[16] Julio J Lucia and Hipòlit Torró. On the risk premium in Nordic electricity futures prices. *International Review of Economics & Finance*, 20(4):750–763, 2011.

[17] Christian Redl and Derek W Bunn. Determinants of the premium in forward contracts. *Journal of Regulatory Economics*, 43(1):90–111, 2013.

[18] Christian Redl, Reinhard Haas, Claus Huber, and Bernhard Böhm. Price formation in electricity forward markets and the relevance of systematic forecast errors. *Energy Economics*, 31(3):356–364, 2009.

[19] Matthäus Pietz. Risk premia in the German electricity futures market. In *Energy and Environment, 2009. ICEE 2009. 3rd International Conference on*, pages 160–170. IEEE, 2009.

[20] Goknur Umutlu, André Dorsman, and Erdinc Telatar. *The Electricity Market, Day-Ahead Market and Futures Market*, pages 109–128. Springer Berlin Heidelberg, Berlin, Heidelberg, 2011.

[21] Hany A Shawky, Achla Marathe, and Christopher L Barrett. A first look at the empirical relation between spot and futures electricity prices in the United States. *The Journal of Futures Markets*, 23(10):931, 2003.

[22] R Core Team. *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria, 2016.

[23] Hadley Wickham. *ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York, 2009.

[24] Helen Higgs and Andrew Worthington. Stochastic price modeling of high volatility, mean-reverting, spike-prone commodities: The Australian wholesale spot electricity market. *Energy Economics*, 30(6):3172–3185, 2008.

[25] European Commission. Reports on European Electricity Markets.

[26] Angel Pardo, Vicente Meneu, and Enric Valor. Temperature and seasonality influences on Spanish electricity load. *Energy Economics*, 24(1):55–70, 2002.

[27] Erik Haugom and Carl J Ullrich. Market efficiency and risk premia in short-term forward prices. *Energy Economics*, 34(6):1931–1941, 2012.