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Risk premia in electricity derivatives markets

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A B S T R A C T

This study examines the prices of options contingent on electricity futures traded on the European Energy Exchange, with the aim to recover the probability density functions and risk premia. After we extract the risk-neutral probability density functions from prices of such options, we transform the risk-neutral densities into real-world densities using both parametric and non-parametric statistical calibration methods and investigate the evolution of risk premia and pricing kernels. We find that both risk-neutral and real-world option-implied densities accurately forecast realized futures electricity prices. Positively skewed densities suggest that there is an inverse (or positive) leverage effect in the electricity market, meaning that a higher probability of large price increases in electricity has been incorporated in the traded option prices. In addition, we find that the state price densities are mostly increasing, implying that investors are more risk-averse to high electricity prices. Over a period of 15 years, our results provide evidence of negative market price of risk and risk premia in this new market.

1. Introduction

Options on futures are options contracts written on the futures price of a financial asset, such as energy products, metals, agricultural commodities, foreign currencies, interest rates and equity indices. Since their introduction in October 1982, futures option markets have experienced significant growth,[1] in terms of both available contracts and trading volume (Zhang et al., 2020; Bhaumik et al., 2016; Simon, 2014). One possible reason for this growth is that investors use options as an efficient tool for their complex trading strategies involving both speculation and risk hedging against fluctuations in the prices of the underlying assets.

Within the energy markets, electricity is a relatively new tradable commodity, with great financial, economic, social and political implications (Weron, 2006). Electricity markets around the world have been subject to increased deregulation and liberalization since the 1990s. A specific characteristic of these markets is that spot prices display extreme price volatility given the difficulty of storing electricity in significant quantities. The dependency of electricity demand on weather conditions (e.g. rain, wind, temperature) and on the intensity of business and everyday activities (e.g. on-peak versus off-peak hours, weekdays versus weekends) can also contribute to such high volatility in spot electricity prices. These features generate price dynamics that are not commonly observed in other financial and energy markets: indeed, electricity prices are subject to severe but short-lived fluctuations, the well-known price spikes. Defined by sudden substantial changes in spot prices, these spikes greatly affect consumers and producers, and can expose energy companies to intense losses and even bankruptcy. Hence, the correct management of the risks linked to abrupt run-ups in prices is critical. Spikes can also send important signals to investors about supply shocks due to insufficient generation capacity or transmission constraints (Nomikos and Soldatos, 2010). If spikes occur with higher frequency, a lack of action from investors has to be replaced by regulatory interventions through incentives for new investments. From a social angle, if consumers are unwilling to absorb even temporarily these spiked prices, then price caps should be introduced to protect them (Weron, 2006).

In contrast to other commodities, electricity is fungible - an economically non-storable good that must be discharged immediately upon production. The lack of storability hinders the no-arbitrage principles, making the pricing of electricity products challenging (Knittel and Roberts, 2005; Michelfelder and Pilotte, 2019). Among others, Geman and Roncoroni (2006), Benth et al. (2008a) and Koten (2020) have

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[1] This trend has been driven by new developments in various market segments such as interest rate markets, equity and energy markets. Following a period of stable growth culminating to 584 million in 2007, the volume of futures options dropped to 374 million in 2009 as a result of the global financial crisis and increased again continuously to 677 million in 2014, reaching 1 billion contracts in 2018 (see Rhoads, 2019). The vital role played by the futures market is confirmed by the fact that US$23 trillion worth of futures were traded in US markets in 2017, with 21% due to the energy sector.

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shown that the risk of operating in a market characterized by extreme volatility and abrupt spikes can be offset by using a range of derivative products traded on power exchanges, such as futures and options.

The present study examines the European electricity derivatives market by estimating the probability density functions (PDFs) implied by option prices written on electricity futures contracts traded on the European Energy Exchange (EEX). This is a valuable technique since density predictions not only allow the computation of important measures such as implied volatility – that reveals market uncertainty, but also convey information on the likelihood of future outcomes for electricity prices. The estimation of PDFs allows operators to infer ex-ante the expected electricity futures prices, to obtain a general overview of the market's expectations about the future and to unveil investors' attitude towards risk. Therefore, estimating the densities from option prices provides unique information about the market sentiment and it can be a useful supplement to other sources of information. This additional information can benefit consumers, producers, financial market participants and decision-makers who need information to gain insights into future financial and economic development.

We contribute to the extant literature on electricity markets in several ways. First, we investigate the electricity market from a different perspective compared to previous studies. While there is a significant amount of research on the relationship between spot and futures electricity prices (Carmona et al., 2012; Cartea and Villaplana, 2008), there are no empirical studies that look at extracting information from the options on electricity futures with the aim to derive the risk premia, the pricing kernels (or stochastic discount factors) and the risk-preferences for investors at the same time.

Second, using a more recent and less researched set of options prices data on the Phelix Base Futures we employ a flexible methodology that leads us to the derivation of the density forecasts over the period September 2010 to February 2017. This methodology has been previously applied to interest rates and equity markets, e.g. Ivanova and Gutiérrez (2014) and Fabozzi et al. (2014), but it received less attention in the literature on energy markets. In particular, we apply the stochastic volatility of Heston (1993) to directly extract the risk-neutral probability densities (RND) and then we use both parametric and non-parametric methods to derive the pricing kernel from options prices on electricity futures, linking for the first time in the literature, asset pricing to derivatives on electricity futures. Given that the estimation of the PDF enables us to recover the entire expected electricity price distribution compared to a single prediction interval, new valuable empirical insights can be obtained from electricity markets.

Third, we try to shed some light on expected futures prices, given that forward-looking option prices reflect market perceptions about underlying asset prices in the future. The forward-looking aspect offers our results a new dimension compared to previous studies where the focus is on the forward risk premia using historical data on spot prices. This could help alleviate some of the problems observed in the spot electricity markets in relation to sudden price spikes.

We attempt to fill the gap in the literature by addressing the following questions: 1) how can we extract the RNDs of electricity futures prices from market prices of futures options; 2) how can we calibrate the pricing kernel linking the martingale pricing measure and the physical measure for electricity futures; 3) what are the characteristics of the risk premia and the shape of the pricing kernel in this important energy market and 4) what can we infer about the market representative agent's risk preferences.

We find that all the estimated risk-neutral and real-world densities are positively skewed, bringing supportive evidence of the presence of the inverse leverage effect in the electricity markets, as opposed to the equity markets. When comparing the estimated density distributions in terms of their peakedness across four different calibration dates, we observe a consistent pattern in their relative position, with the non-parametric real-world density achieving the highest peak, followed by the risk-neutral density and the non-parametric real-world density. Based on formal tests for forecasting accuracy, we show that both risk-neutral and real-world densities forecast accurately the one-month ahead electricity futures prices. With regards to the estimated pricing kernel we infer a rather smooth U-shape for the parametric approach and a U-shape with humps for the non-parametric method. While the spikes seem to remain a feature of the spot electricity prices, these humps in the non-parametric kernel can be interpreted as a manifestation of the initial spikes in the electricity futures markets. Regarding the risk premia, both parametric and non-parametric methods yield a negative risk premia in the electricity markets. This is in contrast with evidence of positive risk premia from equity and currency markets, for example. However, our results have a new dimension given the informational content inherent to the asset class we employ, namely options on electricity futures.

The remainder of this study is organized as follows. Section 2 gives an overview of the relevant literature. Section 3 presents the calibration procedure to extract RNDs from option prices, the methods to transform them into real-world densities and the modelling approach of pricing kernels and risk premia. Section 4 summarizes the main characteristics of the European electricity market and outlines the data used in our study. Section 5 displays the results of the empirical analysis and Section 6 concludes.

2. Literature review on risk premia in electricity markets

While there is a growing literature on the analysis of risk premia in electricity markets, there are no studies dedicated to the recovery of the risk-neutral and real-world density from option prices written on electricity futures contracts. Explicitly, three strands of the literature can be identified. The first draft analyses the *forward* risk premia in energy markets, i.e. it considers forward (futures) and spot prices. The second strand investigates the determinants of forward risk premia, while the third one looks into price modelling and pricing electricity.

The first strand of the literature documents a complex picture regarding the sign and the magnitude of the risk premia in electricity markets, also exploring other attributes such as time-variation and seasonality. The complexity is accentuated by the use (sometimes interchangeably) of different definitions of risk premium.[2] Therefore, great caution must be taken when interpreting the sign of the risk premia in the literature as well as their magnitude.[3]

If the energy market is negatively correlated with the stock market, then the risk premium is expected, on a theoretical basis, to be driven by the link between systemic risk and the futures market, hence, to be negative. However, Pindyck (2001) argued that the majority of industrial related commodities have a positive correlation with the overall economy and, therefore, a positive risk premium is expected. For instance, Longstaff and Wang (2004) analysed the wholesale electricity market in Pennsylvania, New Jersey, and Maryland (PJM) from June 2000 to November 2002 using 2.5 years of day-ahead and real time price data and showed that risk premia may vary throughout the day being either positive or negative. Similar daily patterns were confirmed by Douglas and Popova (2008) and Pirrong and Jermakyan (2008).

For the PJM contract, Cartea and Villaplana (2008) detected clear seasonal patterns, with risk premia being positive during periods of high volatility of demand, and negative during months of low volatility of demand when forwards may trade at a discount. Despite some sensitivity in the estimated models to seasonality, Haugom and Ullrich (2012) found evidence that the forward prices are both unconditionally and conditionally unbiased forecasts of the expected spot prices. For the same PJM market, Michelfelder and Pilotte (2019) presented evidence

[2] We encounter in the literature several terms related to risk such as risk premium, forward premium, forward risk premium and market price of risk; in addition, there are studies that examine ex-post (or realized) premia, and others that focus on expectations of the spot price to compute ex-ante premia. For a comprehensive discussion see Weron and Zator (2014)

[3] See Junttila et al. (2018) for a similar discussion.

of statistically significant median risk premia that are positive, implying that overall sellers of day-ahead forward contracts earn a positive premium from buyers. In addition, they argued that the non-storability of electricity breaks up the standard cost-of-carry no-arbitrage link between forward prices and spot prices and, thus, the former are the sum of the latter and a *forward* risk premium. They also pointed out that the sign and size of the risk premium is influenced by "hedging pressures" such as the degree to which hedgers are overall short or long. Similarly, Bessembinder and Lemmon (2002) asserted that forward risk premium in the electricity markets may vary in both magnitude and sign depending on the asymmetric hedging needs of producers and retailers.

As part of the Nordic market, the Finnish electricity futures market has displayed signs of inefficiency as the shocks in the spot electricity market did not transmit efficiently to the futures market, hence hedgers and speculators could not benefit economically despite a substantial increase in the trading volume over the last decade Junttila et al., 2018). The authors also found evidence of positive futures premium during autumn and winter, and negative during summer. Huisman and Kilic (2012) showed that the risk premium is time-varying on monthly contracts in the Dutch market, but it is not on the Nordic electricity market. Based on futures with a four-week delivery period, Weron (2008) estimated that forward risk premia in the Nordic market are positive and increasing with time to maturity due to the incentive for hedging on the demand side relative to the supply side and to the non-storability of electricity. Lucia and Torró (2011) detected significant positive risk premia in weekly Nord Pool futures between 1998 and 2007. Conversely, Botterud et al. (2010) documented negative forward risk premia for all holding periods in this market, the overall results being in line with Weron and Zator (2014). Redl et al. (2009) identified negative forward risk premia for month-ahead contracts in the Nord Pool and the EEX.

For the EEX market based on data covering the period October 2005 to September 2008, Viehmann (2011) found that market participants are risk-averse and pay significant (ex-post) risk premia in periods of low demand and positive risk premia during peak hours. Wilkens and Wimschulte (2007) and Kolos and Ronn (2008) documented positive risk premia on the German EEX market, while Benth et al. (2014) separated their analysis of risk premium into base load and peak load prices and detected an overall negative risk premium for longer maturities and a positive risk premium for near delivery contracts. Studying the electricity prices at the European Power Exchange and Energy Exchange Austria, Valitov (2019) discovered that the appearance of negative prices in 2008 for the former and in 2013 for the latter contributed to a reduction in the (ex-post) risk premia. In addition, Paraschiv et al. (2015) presented evidence that short-term risk premia are mainly positive during the week, while decreasing into negative territory for the weekend. For the Phelix contract in Germany, Benth and Paraschiv (2018) applied a space-time random field model and computed risk premia taking values between −0.086 and 0.017, being predominantly negative for the medium and long time to maturity, while varying around zero for short maturities. Regarding the New Zealand electricity market, Bevin-McCrimmon et al. (2018) documented time-varying risk premia induced by inefficient market participants' behaviour. Within this strand, all the previous studies have analysed risk premia considering forwards (futures) and spot electricity prices. Our investigation, however, is on the risk premia derived from options on electricity futures, an asset class which offers our results a new forward-looking dimension.

The second strand of the literature examines forward risk premia in energy markets from another angle trying to identify its possible drivers. The measurement of the electricity risk premium is extremely challenging, reflecting the multitude of factors that may affect its evolution. Hence, variation in any of these factors may significantly impact the level and/or direction risk premia. Bessembinder and Lemmon (2002) claimed that the forward risk premium is negatively related to the variance and positively related to the skewness of expected electricity spot prices, but Koten (2020) could find only partial empirical support in a recent replicating study. Longstaff and Wang (2004) made a link between the risk premium on electricity markets and the volatility of unexpected changes in demand, spot prices, total revenues and the electricity transmission system capacity limit. In a seminal paper on forward contracts in power markets, Benth et al. (2008b) proposed a framework linking the market risk premium to the risk preferences of representative market agents. There is empirical evidence also of a nexus between the forward risk premia and the storability of related energy commodities such as natural gas (Douglas and Popova, 2008; Bloys van Treslong and Huisman, 2010) and supply type - hydro, wind or solar power (Huisman and Kilic, 2012). High inventory levels tend to reduce risk premia particularly in the very warm and cold periods. Furthermore, both sign and magnitude of risk premia may change between long and short positions in a futures contract, they can be time-varying and calculations could be specific to the period of study.

The last strand of the literature has been devoted to modelling electricity prices and pricing electricity derivatives. Modelling of spot electricity prices is challenging due to the occasional spikes and other major idiosyncrasies (Carmona and Coulon, 2013). Mean-reverting models dominate the empirical work on this asset class, e.g. Benth et al. (2007), Benth et al. (2008a), Nomikos and Soldatos (2010). Kiesel et al. (2009) extended the work of Clewlow and Strickland (1999) and Benth et al. (2008a) and proposed an explicit two-factor model that could be calibrated to option price data. The first factor was driven by the increased trading activity as knowledge about weather and unexpected outages became available, while the second factor dealt with the long-term uncertainty driven by technological advances, political changes price developments in other commodity markets. A semi-closed formula option pricing model was derived by Nomikos and Soldatos (2010), who incorporated two different speeds of mean-reversion: one for the diffusion part of the model and one for the spikes. Their option model successfully captured the fast decay of the jumps and indicated that the spikes have an isolated effect on the spot prices without spilling over in the forward markets. Motivated by the introduction of carbon markets, Carmona et al. (2012) used a structural model instead of reduced-form one to price clean spread options. Moreover, based on four case studies, the authors have highlighted the complexity of the price-setting mechanism in the electricity markets by considering the joint dynamics of electricity, fuels and emission allowances. In a more recent paper, Paraschiv et al. (2015) considered a regime-switching model to simulate price paths and forecast forward prices for electricity, over short and medium-term horizons. Furthermore, heavy-tails in electricity prices were captured by Paraschiv et al. (2016) with an extreme value theory model. The forecasts were for short-term horizons and they were determined by models of the spot electricity prices.

Across all the considered strands of the literature, most studies have investigated electricity forward premia (i.e. the excess of the forward price over the expected spot price) or their determinants, but not the risk premia derived from options. We fill the gap in the literature by examining options on electricity futures, and by calibrating together the risk-neutral and real-world probability densities for these electricity options.[4] Differently from previous studies where only one method is used (e.g. Longstaff and Wang, 2004), our analysis is based on both parametric and non-parametric methods. Therefore, we can estimate and compare the shape of the two corresponding pricing kernels. The methodology employed in our paper is computationally flexible, allowing the direct computation of the electricity risk premium, the market risk premium and the pricing kernel at the same time. The suitability of the option pricing model that we employ is verified based on a forecasting exercise. We believe that this is a necessary intermediary

[4] A similar approach has been applied before in equity (e.g. Fabozzi et al., 2014) and in interest rate markets (e.g. Ivanova and Gutiérrez, 2014).

process before drawing conclusions on other important quantities of interest such as pricing kernel and risk premia.

3. Methodology

There has been great interest among policy-makers in extracting information from the prices of financial assets. Options prices in particular, have proved to be a rich source of information since they enable the extraction of a complete implied risk-neutral probability density function for the commodity prices and other assets of interest. RNDs have proven extremely useful in interpreting the market's assessment of the balance of risks associated with future movements in asset prices. In addition, the estimations of the RND and its pricing kernel counterpart allow an easily computation of the risk premium and the risk aversion coefficient capturing the representative market agent risk preferences.

To estimate the RND of an asset, one can use parametric methods, as in Liu et al. (2007) and Fabozzi et al. (2014), to name just a few, or non-parametric methods, as in Aït-Sahalia and Lo (1998) or Bliss and Panigirtzoglou (2004). RNDs cannot generate on their own risk premia since they represent only a tool to price financial derivatives. Given that investors require a premium that compensates them for the price risk, transformations from the risk-neutral to the so-called real-world density are required. The transformations applied to the RND with the aim of obtaining density forecasts under the real-world measure are often developed in a consumption-based framework and rely on utility transformations (see for instance Rosenberg and Engle, 2002; Bliss and Panigirtzoglou, 2004). Moreover, densities extracted from option prices are shown to have a superior forecasting power over the historical densities (Liu et al., 2007; Shackleton et al., 2010).

3.1. Risk–neutral densities

We use the stochastic volatility model of Heston (1993) to describe the behaviour of electricity futures prices under the risk-neutral measure. Let p_t be the futures price at time t. We assume that $\{p_t\}_{t\geq 0}$ follows a square-root process:

$$\begin{aligned} \mathrm{d}p_t &= p_t\sqrt{V_t}\mathrm{d}W^{\mathbb{Q}}_{t,1} \\ \mathrm{d}V_t &= \kappa(\theta - V_t)\mathrm{d}t + \sigma\sqrt{V_t}\mathrm{d}W^{\mathbb{Q}}_{t,2} \end{aligned} \tag{3.1}$$

where V_t is the stochastic variance and $\mathrm{d}W^{\mathbb{Q}}_{t,1}$ and $\mathrm{d}W^{\mathbb{Q}}_{t,2}$ are increments of two Wiener processes with ρ being the correlation between the two of them. The model has five parameters $\vartheta = (\kappa,\theta,\sigma,\rho,V_0)$. We opt for the above model for two reasons. Firstly, the model is flexible enough to capture stylized features of option prices, such as "smile" effects in implied volatilities. Secondly, the model leads to closed-form densities and theoretical option prices, therefore facilitating the calibration.

The time t price of a European call option with strike K and maturity T, is given by:

$$call_t(K;\vartheta) = \mathrm{e}^{-r(T-t)}(p_tP_1 - KP_2) \tag{3.2}$$

where r is the risk-free rate (EURIBOR), P_2 and P_1 are probabilities that the option expires in-the-money under the risk-neutral measure and under a different measure, respectively, as described for instance in Ch. 5 of Vainberg and Rouah (2007). The risk-neutral density of p_T, denoted by $f_Q(\cdot)$, can be derived from its characteristic function[5] $g(\omega) = \mathbb{E}^{\mathbb{Q}}[\exp(\mathrm{i}\omega\log p_T)]$ by numerical integration:

$$f_Q(x) = \frac{1}{\pi x}\int_0^\infty \mathrm{Re}\left[\exp(-\mathrm{i}\omega\log x)g(\omega)\right]\mathrm{d}\omega. \tag{3.3}$$

At each calibration date t, we estimate ϑ on a cross-section of N_t options all maturing at time T by minimizing the sum of squared differences between theoretical and market prices:

$$\arg\min_{\vartheta}\sum_{i=1}^{N_t}\left[call_t(K_i,\vartheta) - call_t^{mkt}(K_i)\right]^2, \tag{3.4}$$

where $call$ denotes the theoretical price and $call^{mkt}$ represents the observed market price.

3.2. Real–world densities

Since option implied distributions are risk-neutral, they do not incorporate risk premia. This means that in a risk-neutral world, the prices of any derivative do not reveal anything about market participants' risk preferences. However, given that investors are not risk-neutral and require a premium for bearing the risk, we adopt the calibration method proposed by Fackler and King (1990) (see also Diebold et al., 1999) to move from risk-neutral to real-world densities. This transformation allows us to infer the investors' risk preferences.

Let $F_Q(\cdot)$ be the cdf risk-neutral distribution function of p_T and $U_T = F_Q(p_T)$ the probability integral transform (PIT) with its cumulative distribution function $C(\cdot)$. Then, the real-world distribution function, $F_P(\cdot)$, is related to the risk-neutral distribution function $F_Q(\cdot)$ as follows:

$$F_{\mathbb{P}}(x) = \mathbb{P}(p_T \le x) = \mathbb{P}\left(F_Q(p_T) \le F_Q(x)\right) = \mathbb{P}\left(U_T \le F_Q(x)\right) = C\left(F_Q(x)\right) \tag{3.5}$$

The real-world cdf density is then obtained as:

$$f_P(x) = \frac{\partial}{\partial x}F_P(x) = \left(\frac{\partial}{\partial x}F_Q(x)\right)\left(\frac{\partial}{\partial F_Q(x)}C\left(F_Q(x)\right)\right) = f_Q(x)c\left(F_Q(x)\right),$$

where $c(\cdot)$ is the probability density of U_T. It is well known (e.g. Diebold et al., 1999) that when the risk-neutral density is correctly specified, U_T has a standard uniform distribution. In this case $C(u) = u$ and (3,5) implies that the risk-neutral and real-world distribution functions coincide. Since, in general, this is not the case, $C(\cdot)$ is interpreted as a calibration function that enables researchers to convert the RND density into a real-world density. As described in the next sections, we consider a parametric method based on the beta distribution and a non-parametric method to estimate it.[6]

As documented by Diebold et al. (1998), a two-parameter beta distribution is not flexible enough, therefore we also consider a non-parametric approach for the calibration function. Although it is more flexible, the non-parametric approach is sensitive to the choice of the bandwidth parameter, for which econometricians face the usual trade-off between bias and variance (e.g. Härdle, 1990).

3.2.1. Parametric approach

Fackler and King (1990) proposed using the beta distribution as the calibration function. For this choice,

$$C(u) = \frac{u^{a-1}(1-u)^{b-1}}{B(a,b)}$$

where $B(\cdot,\cdot)$ is the beta function. Hence, the real-world probability density function is given by:

$$f_P(x) = f_Q(x)\frac{F_Q(x)^{a-1}\left(1-F_Q(x)\right)^{b-1}}{B(a,b)}. \tag{3.6}$$

Note that eq. (3.6) includes the standard uniform distribution as a special case corresponding to $a = b = 1$. The estimated parameters $\widehat{a}$ and $\widehat{b}$

[5] The formula for the characteristic function of $\log p_T$, conditional on p_0 and V_0, can be found in Heston (1993) and Bakshi et al. (1997), among others.

[6] See Shackleton et al. (2010).

are obtained by maximizing the log-likelihood function of the observed futures prices at the option maturity:

$$\left(\widehat{a}_t,\widehat{b}_t\right)=\arg\max_{a,b}\sum_{i=0}^{t-1}\log\left(f_P(p_{i+1}|a,b)\right). \tag{3.7}$$

3.2.2. Non-parametric approach

The non-parametric calibration method is based on the risk-neutral probabilities $u_{i+1}=F_Q(p_{i+1})$, for $i=0,1,\ldots,t-1$ and it assumes that the observations are i.i.d. with a distribution function equal to the calibration function $C(\cdot)$ through kernel density estimation. As in Shackleton et al. (2010), we apply a normal kernel to $y_i=\Phi^{-1}(u_i)$, i.e. to the variables u_i transformed using the inverse of the standard normal cumulative distribution. The kernel density is computed as:

$$\widehat{h}(y)=\frac{1}{t\lambda}\sum_{i=0}^{t-1}\varphi\left(\frac{y-y_{i+1}}{\lambda}\right)$$

and therefore its cdf is equal to:

$$\widehat{H}(y)=\frac{1}{t}\sum_{i=0}^{t-1}\Phi\left(\frac{y-y_{i+1}}{\lambda}\right)$$

where $\varphi(\cdot)$ denotes the standard normal density function, the bandwidth λ is computed according to the standard formula of Silverman (1986), $\lambda=0.9\sigma_y/t^{0.2}$, and σ_y denotes the standard deviation of the series $\{y_i\}_{i=1}^t$. The calibration function is estimated as:

$$\widehat{C}(u)=\widehat{H}\left(\Phi^{-1}(u)\right).$$

From (3.5), the real-world distribution function is given by:

$$F_P(x)=\widehat{C}(u),\quad \text{with}\quad u=F_Q(x).$$

Using the fact that $\frac{\partial}{\partial u}y=\frac{\partial}{\partial u}\Phi^{-1}(u)=\frac{1}{\varphi\left(\Phi^{-1}(u)\right)}=\frac{1}{\varphi(y)}$, the real-world density is obtained as follows:

$$\begin{aligned}f_P(x)&=\frac{\partial}{\partial x}\widehat{C}(F_Q(x))=\frac{\partial}{\partial x}\widehat{H}\left(\Phi^{-1}(F_Q(x))\right)\\&=\frac{\partial u}{\partial x}\frac{\partial y}{\partial u}\frac{\partial\widehat{H}(y)}{\partial y}=f_Q(x)\frac{\widehat{h}(y)}{\varphi(y)}.\end{aligned}$$

Like in the parametric approach, the estimation is performed at the end of each period t using all the available data until that point in time.

3.3. Evaluating density forecasts

In this section, we present formal testing procedures to assess the accuracy of density forecasts and establish whether real-world option-implied densities have a superior forecasting power over the risk-neutral ones. We first present the procedure of Berkowitz (2001), designed to test the null hypothesis that the estimated densities are the true densities. Since under the null the PITs are uniform and independent, Berkowitz (2001) proposed calculating $z_i=\Phi^{-1}(u_i)$ and testing whether the z_i are independent and standard normal, with Φ^{-1} being the standard normal quantile function. This is done by estimating the following AR(1) model:

$$z_i-\mu=\rho(z_{i-1}-\mu)+\epsilon_i,\qquad \epsilon_i\sim i.i.d.N\left(0,\sigma^2\right). \tag{3.8}$$

Under the null hypothesis, the parameters of the above model take on values $\mu=\rho=0$ and $\sigma^2=1$. Hence, denoting by $L(\mu,\sigma^2,\rho)$ the log-likelihood of the model, the test statistic is given by the likelihood ratio:

$$LR_3=-2\left[L(0,1,0)-L\left(\widehat{\mu},\widehat{\sigma}^2,\widehat{\rho}\right)\right]$$

where $\widehat{\mu}$, $\widehat{\sigma}^2$, and $\widehat{\rho}$ are the maximum-likelihood estimates from (3.8). The test statistic has a chi-squared distribution with three degrees of freedom. If one is only interested in the independence hypothesis, i.e. in testing the null that $\rho=0$, the test statistic is given by the likelihood ratio $LR_1=-2\left[L\left(\widehat{\mu},\widehat{\sigma}^2,0\right)-L\left(\widehat{\mu},\widehat{\sigma}^2,\widehat{\rho}\right)\right]$ and has a chi-squared distribution with one degree of freedom.

In addition, we implement the procedure proposed by Amisano and Giacomini (2007), which aims to detect if the differences between the accuracy of forecasts provided by different densities are significant. We start with the sequence of log-returns for Phelix Futures established on calibration at t_i for options maturing at time T_i, i.e. $y_i=\log\left(p_{T_i}/p_{t_i}\right)$, $i=1,\ldots,n$. Given the weight function $w(\cdot)$ and two alternative density forecasts f_1 and f_2 for y_i, we compare weighted averages of the logarithmic scores via

$$WLR_i=w\left(y_i^{st}\right)\left[\log\left(f_1(y_i)\right)-\log\left(\mathrm{f}_2(\mathrm{y}_i)\right)\right], \tag{3.9}$$

where y_i^{st} is the standardized version of y_i. Given $\overline{WLR}=\frac{1}{n}\sum_{i=1}^n WLR_i$, the null hypothesis, that the two forecasting methods have equal expected log-likelihood, is tested using the test statistic

$$AG=\frac{\overline{WLR}}{\widehat{\sigma}_n\sqrt{n}} \tag{3.10}$$

where $\widehat{\sigma}_n^2$ is a heteroskedasticity and autocorrelation consistent estimator of $\sigma_n^2=var\left(\sqrt{n}\overline{WLR}\right)$. The test statistic is asymptotically standard normal.

3.4. Pricing kernels

Recall that option prices are obtained as the expectation under the risk-neutral measure of the discounted payoff (using the risk-free rate). For instance the price of a call option is given by:

$$call=\mathbb{E}^Q\left[\mathrm{e}^{-rT}(p_T-K)^+\right]=\int_0^\infty \mathrm{e}^{-rT}(x-K)^+f_Q(x)\mathrm{d}x. \tag{3.11}$$

To obtain the same price as the expectation under the real-world measure, a stochastic discount factor or pricing kernel has to be used. Indeed, the terms inside the integral in (3.11) can be adjusted to obtain

$$call=\int_0^\infty m(x)(x-K)^+f_P(x)\mathrm{d}x=\mathbb{E}^P\left[m(p_T)(p_T-K)^+\right], \tag{3.12}$$

where the pricing kernel $m(x)$ satisfies for each $x>0$ the condition:

$$m(x)=\frac{\mathrm{e}^{-rT}f_Q(x)}{f_P(x)}. \tag{3.13}$$

The pricing kernel reflects how investors evaluate possible states of nature and their expectations of the probability of those states happening. Thus, the difference between the real-world and the risk-neutral distributions stems from the fact that investors with different risk profiles give different importance to wealth in different states of the world. In the case of risk-averse investor, an increase in wealth in states where he/she is already wealthy is valued less than in low-wealth states. The pricing kernel can be interpreted as the price assigned by investors to one unit of wealth in different states of the world at the option maturity.

3.5. Risk Premia in electricity derivatives markets

In this section, we discuss the risk premia embedded in the electricity derivatives, namely options on futures. Assuming that the risk-neutral dynamics of futures prices is given by (3.1) and if $\{\lambda_t\}_{t\geq 0}$ denotes the market price of risk process, it follows that

$$W^P_{1,t} = W^Q_{1,t} - \int_0^t \lambda_u \mathrm{d}u,$$

and then the log-futures price obeys the following real-world dynamics:

$$\mathrm{d}\log p_t = \left(\lambda\sqrt{V_t} - V_t/2\right)\mathrm{d}t + \sqrt{V_t}\mathrm{d}W^P_1.$$

We measure risk premia as the expected log-futures price under the real-world measure minus expected log-futures price under the risk-neutral measure. Under our modelling approach, this is given by

$$\mathbb{E}^P[\log(p_T/p_0)] - \mathbb{E}^Q[\log(p_T/p_0)] = \int_0^T \lambda_u \sqrt{V_u}\mathrm{d}u. \tag{3.14}$$

Eq. (3.14) implies that the considered measure of risk premia has the same sign of the market price of risk λ and it establishes an analytical connection that is computationally easy to follow between the two types of risk.[7] Note that the market price of risk represents the excess return an investor requires to carry an additional unit of risk.

4. Market outlook and data

4.1. Electricity exchanges

Following the liberalization of electricity markets and the reduction of government controls over electricity generation and distribution in the 1990s, several exchanges[8] have been created to trade physical and futures contracts.

As the most active trading market, EEX[9] has become the leading energy exchange in continental Europe in terms of sales and number of trading participants (see www.eex.com). Based in Leipzig, the EEX is a platform for trading power, natural gas, emission rights (CO2) and coal, covering both spot and derivatives markets. The EEX derivatives market offers electricity derivatives instruments contingent on futures electricity prices or price indices. In particular, it offers futures with cash settlement (Phelix futures), futures with physical settlement (Power futures) and options on financial futures (Phelix options). Settled against the average power spot market prices of future delivery periods for the German/Austrian market area, Phelix Futures are the most liquid contracts and a benchmark for European Power trading.

The underlying of the (cash settled) futures[10] is the daily Phelix Index (Physical Electricity Index) that is calculated from EPEX spot market data on a daily basis. The EEX also offers European options contracts written on the Phelix Base futures with monthly, quarterly and yearly delivery periods, while the exercise dates are placed four trading days prior to the beginning of the delivery period of the underlying futures.

[7] Pirrong and Jermakyan (2008) extract the unknown market price of risk from market prices using inverse methods. Market price of risk is then the main driver for pricing more exotic derivatives in the same market.

[8] Starting with the oldest one, the Nord Pool in Scandinavia, a list of leading electricity exchanges includes EEX in Germany, Powernext in France, EPEX in Central Western Europe and the UK, EXAA in Austria, GME and IPEX in Italy and OMEL in Spain.

[9] The process of integration among European power networks spurred by the European Commission has facilitated the consolidation among exchanges. In October 2009, the EEX and Powernext boards approved a cooperation agreement between the exchanges to create a pan-European power spot market (EPEX) for France, Germany-Austria and Switzerland.

[10] Electricity futures can be physical – i.e. the delivery is obligatory, or financial - i.e. the contract will be cash-settled. Unlike other futures contracts which are either one or the other, the two types of contract often trade in parallel.

Table 1
Descriptive statistics of futures and spot EEX Phelix electricity prices and log-returns between 1 July 2002 and 28 February 2017.

	Daily prices		Monthly prices	
	Phelix Futures	Phelix Spot	Phelix Futures	Phelix Spot
Mean	41.6567	43.7061	41.0780	41.7539
Median	38.4500	40.6600	38.4650	38.7500
Standard Deviation	13.4352	17.5810	13.1671	16.3223
Kurtosis	1.0404	19.0705	1.5205	5.5592
Skewness	1.0252	2.3545	1.1692	1.5780
Range	77.6100	358.4100	66.8200	124.7100
Minimum	20.8000	−56.8700	22.4100	8.2000
Maximum	98.4100	301.5400	89.2300	132.9100
	Daily log-returns		Monthly log-returns	
	Phelix Futures	Phelix Spot	Phelix Futures	Phelix Spot
Mean	0.0001	0.0005	0.0025	0.0008
Median	−0.0004	0.0000	0.0123	0.0124
Standard Deviation	0.0274	0.2283	0.1423	0.3920
Kurtosis	17.7322	26.4505	1.5590	4.5606
Skewness	1.3380	0.3705	−0.0296	−0.3977
Range	0.4634	5.4935	0.9707	3.2454
Minimum	−0.1875	−2.8180	−0.3776	−1.9269
Maximum	0.2758	2.6755	0.5931	1.3185

Note: We eliminated 16 daily observations corresponding to negative spot prices, out of the total of 4348 observations.

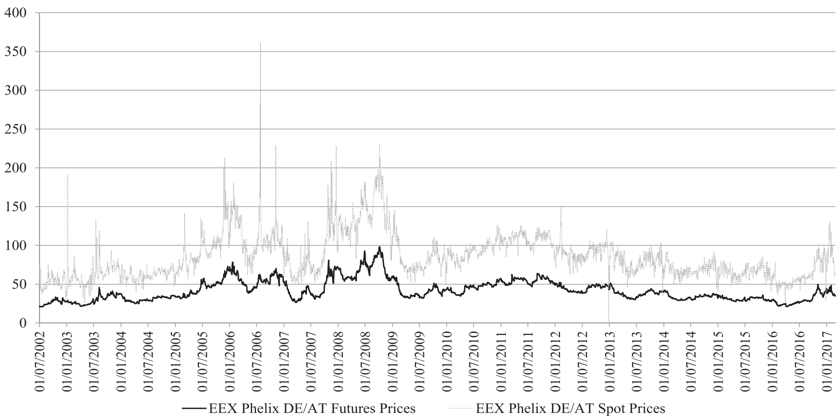
4.2. Data sets

In the first stage of the analysis, we examine the daily and monthly time series of Phelix futures and spot electricity prices, extracted from Thomson Reuters Eikon, for the period 1st of July 2002 to 28 February 2017. These data describe the underlying asset of the options examined in the second stage of the analysis. Daily data was chosen because it is the highest frequency available, while the monthly frequency has been selected to match the maturity of the options used to derive the probability densities.

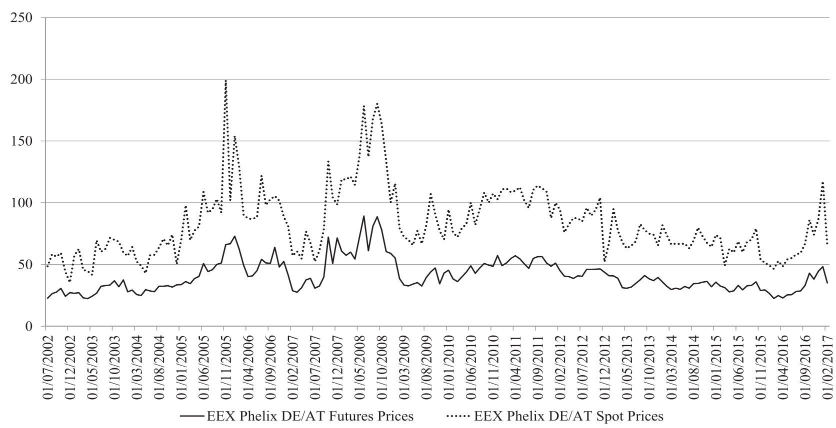
Table 1 reports the descriptive statistics of the futures and spot Phelix electricity prices (S), at daily and monthly frequencies and the respective log returns (R), computed as $R_t = \ln(S_t) - \ln(S_{t-1})$. The average daily Phelix spot prices are slightly higher than Phelix Futures prices and almost equal for monthly data. Specifically, the average daily spot prices amounted to 43.71 EUR/MWh, and the average futures prices was 41.66 EUR/MWh. Spot prices are also more volatile than futures prices. This occurs because inventories cannot be used to smooth supply or demand shocks as explained by Bessembinder and Lemmon (2002) and Huisman and Kilic (2012). Another important aspect of spot prices in wholesale markets is that they can have negative values. Electricity spot price varied on a daily basis between −56.87 EUR/MWh and 301.54 EUR/MWh.

Surprisingly, negative electricity prices have economical sense and can contain important incentive signals for load-shifting. Producers would pay consumers when electricity demand is very low and production is relatively high, as this is more profitable than temporarily shutting down the plants (Branger et al., 2010). Prices have positive skewed distributions, suggesting frequent small price drops and few extreme price run-ups (Algieri and Leccadito, 2019). In addition, a greater skewness in the spot market compared to futures market represents a greater chance of price spikes in the cash market (Bevin-McCrimmon et al., 2018). Returns show similar dynamics: they are more volatile for spot contracts and less volatile for the corresponding futures contracts at both daily (22.8% for spot versus 2.74% for futures) and monthly frequency (39.20% for spot versus 14.23% for futures).

The most striking differences between the futures and spot electricity series are in terms of kurtosis and range, with a particularly high difference for the latter. This is in line with the observation made by Nomikos and Soldatos (2010) that the futures time series may not exhibit extreme spikes that are usually associated with spot electricity



(a) Daily Phelix Futures and Spot Prices



(b) Monthly Phelix Futures and Spot Prices

Fig. 1. Comparison of Phelix Futures and Spot Prices traded on EEX over the period 1 July 2002 to 28 February 2017.

markets; that is, the spikes effects do not spill-over to the forward/futures market. This is corroborated by Fig. 1. Implicitly, modelling futures prices does not necessarily require models to account for spikes and therefore, utilising models from the Heston family that capture stochastic volatility really well, could bring clear computational benefits.

In the second stage of the analysis, we consider the settlement prices of Phelix Options for the period from September 2010 to February 2017. Our sample has 78 trading days in which contracts with maturity closest to one month are observed.

Table 2
Summary of European call and put Phelix DE/AT Options (EEX Power Derivatives).

Moneyness $K/p_t - 1$	Percentage	Average IV	Average CallPrice(€)	Average PutPrice(€)
(−0.3,-0.2]	0.0518	0.3534	10.2101	–
(−0.2,-0.1]	0.1586	0.2931	5.8818	–
(−0.1,0]	0.2298	0.3028	2.5963	–
(0,0.1]	0.2184	0.2648	–	2.6634
(0.1,0.2]	0.2006	0.2545	–	6.1961
(0.2,0.3]	0.1408	0.2680	–	9.5841

Note: Moneyness is defined as option strike divided by the price of the underlying futures contract. For each moneyness category, the table reports the percentage of the total observed data points (second column), the average implied volatility (third column), the average call option price (fourth column), and the average put option price (fifth column).

Our dataset includes settlement prices of options with underlying Phelix Base monthly futures maturing two months after each considered trading day, so that when the option expires the underlying futures contract has a time to maturity of approximately one month. For instance, one trading day on which we observe option prices is 26 June 2013. On that particular day, we select options maturing on 26 July 2013 written on the futures contract with delivery in August 2013.

We filter out from our dataset all the unreliable data points, retaining only options satisfying the following conditions (1) with moneyness[11] $|K/p_t - 1| \leq 0.30$; (2) with price above the lower bound, i.e. $\max(0,(K-p_t)e^{-r\tau})$ for put options and $\max(0,(p_t-K)e^{-r\tau})$ for call options, with τ being the option time to maturity; and (3) that verify the property of call (put) prices being decreasing (increasing) in the exercise price. Finally, in order for a given trading day to have contracts with different strikes we keep put options with positive log moneyness and call options with negative log moneyness. This filtering procedure is based on Rosenberg and Engle (2002). Thus, we retain 1236 different contracts prices (on average about 15 prices for each trading day).

Table 2 reports the descriptive statistics in terms of moneyness and implied volatility (IV) for our sample of Phelix Base options. Between September 2010 and February 2017, the average price of a European call option ranged between 2.6 euro and 10.2 euro, and the average

[11] Moneyness is defined here as the ratio of an option's strike price to the underlying asset's current price.

price of a European put option ranged between 2.7 euro and 9.6 euro. In terms of moneyness, we observe an uneven distribution of contracts, relatively equal for moneyness around zero, (in the ranges [−0.1; 0] and [0; 0.1]), but with almost three times more contracts for moneyness between 0.2 and 0.3 compared to the percentage of contracts with moneyness between −0.3 and −0.2. The average implied volatility (IV) reported in each bucket given by moneyness is decreasing with moneyness, from a high value of 35.34% for the lowest moneyness range to 26.80% for the largest moneyness. This indicates that options have not stable but changing implied volatility. This variability in volatility suggests that the Heston model based on stochastic volatility seems well suited to tackle the difficulties of risk-neutral density reconstruction for this particular asset class.

5. Empirical analysis

In this section, we first recover the risk-neutral density for electricity futures over the entire period of study. We then derive the pricing kernel and analyse its evolution over time. Finally, we compute the risk premia under both parametric and non-parametric methods and show that the risk premium is consistently negative for the entire period.

5.1. Empirical results: risk-neutral and real-world densities

Given the set of n expiration times, $\{T_i\}_{i=1,\ldots,n}$, we first construct a series of empirical densities $f_Q\left(p_{T_i};\widehat{\vartheta}\right)$ under the risk-neutral measure. The densities do not overlap, in the sense that for every i, $t_i < T_i \leq t_{i+1}$, with t_i being the time when the density is formed for options that expire at time T_i. For each maturity, we also keep track of the futures value at the option maturity, p_{T_i}. We then compute the real-world density with the parametric and non-parametric approach using an expanding window where the length of the first window is 12,[12] so that the first real-world density is formed on August 2011.

Fig. 2 illustrates the evolution over time of the calibrated parameters obtained using the parametric method based on the beta distribution. We remark that each pair of estimated parameters is obtained by adding at each date a new set of options and a new futures price at the maturity of the option in the optimization problem. The parameter estimates are relatively stable over time, with more variation in the parameter a.

In Fig. 3 we plot both risk-neutral and real-world densities (parametric and non-parametric) for 25 May 2012, 27 June 2014, 24 July 2015, and 25 October 2016. The parametric real-world densities are generally more peaked than risk-neutral densities, meaning that there is a higher probability of having price spikes; while non-parametric real-world densities are less leptokurtic, implying that there are fewer outliers or price spikes. All densities are positively skewed suggesting that a higher chance (probability) of large increases in the future electricity price has been included in the traded option prices, which can be explained by fear of major problems in the electricity market. The positive skewness implies an inverse (or positive) leverage effect in the electricity market (see also Geman and Roncoroni, 2006), meaning that prices and volatility are positively correlated. Hence, if volatility increases when electricity prices surge, then the probability for even higher prices increases. This contrasts with what is observed in equity markets, where negative shocks on returns increase volatility more than positive shocks with the same size, and thus prices and volatility are negatively correlated. A potential cause for a positive skewness is that the electricity supply exhibits convex marginal production costs increasing with the output[13] and, as a consequence, positive demand shocks should affect price changes more heavily than negative shocks (Bessembinder and Lemmon, 2002; Knittel and Roberts, 2005). The inverse leverage effect can also be explained by an increased fear of a surge in electricity prices, as opposed to a price decline. The few studies on RNDs extracted from option prices on energy commodities have documented a positively skewed probability density. For instance, Melick and Thomas (1997) found that crude oil options on futures displayed positive density skewness consistent with the market situation at the time of the Persian Gulf crisis. Doran and Ronn (2005) also detected a positive correlation between price-returns and volatility in energy markets using options on crude oil, heating oil and natural gas.

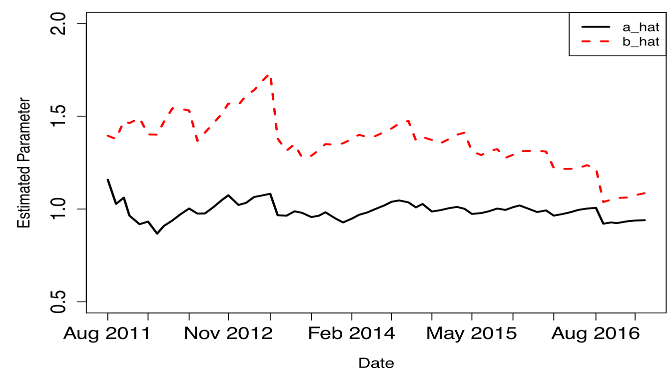


Fig. 2. The evolution of Calibrated Parameters for the beta distribution applied to the RND of Phelix futures. *Note*: The estimated parameters are obtained by maximizing the log-likelihood function (3.7).

5.2. The accuracy of density predictions

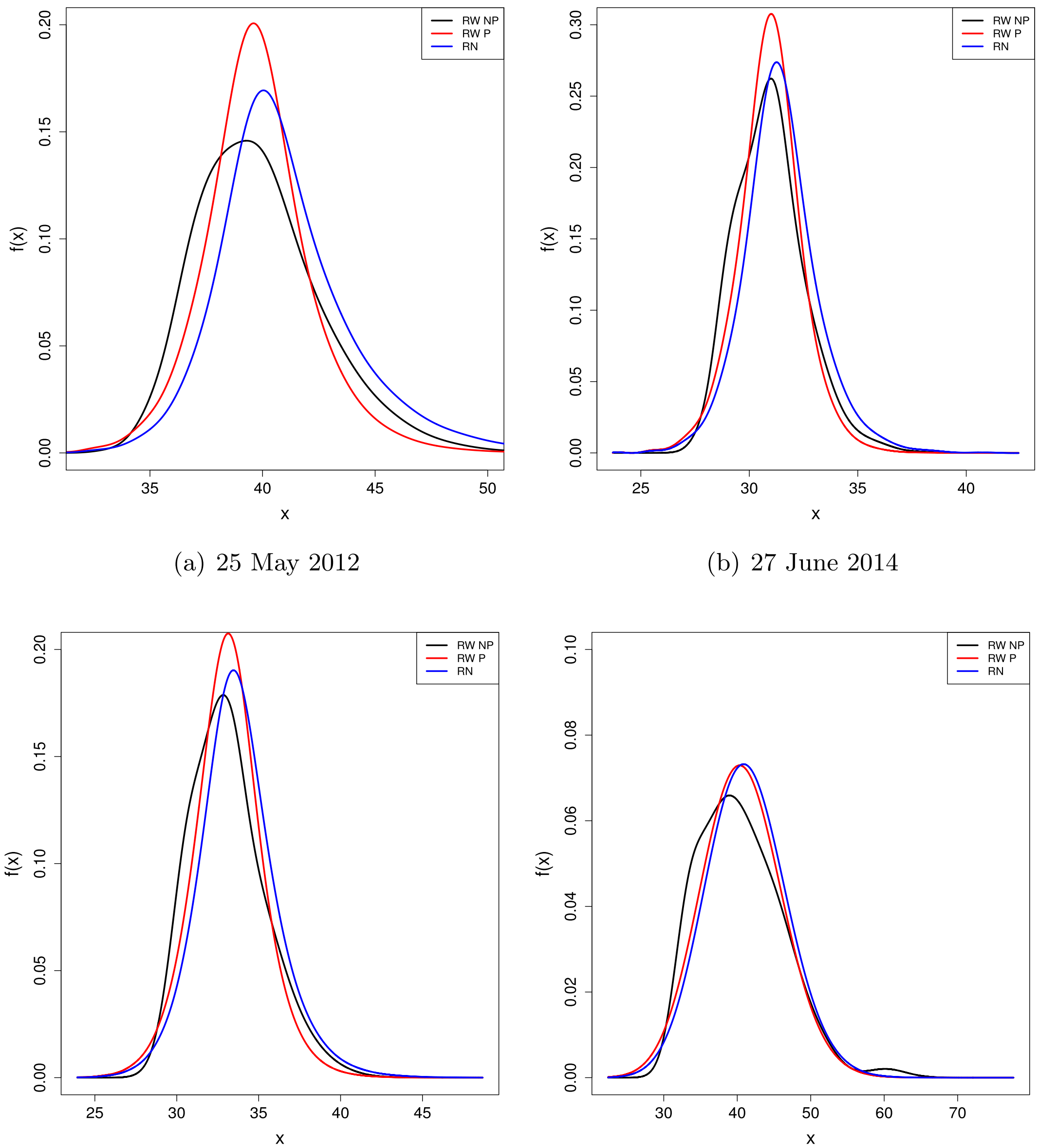
We assess the validity of the density forecasts under the risk-neutral and real-world measures by considering the probabilities $u_i = F_Q(p_{T_i})$ and $u_i = F_P(p_{T_i})$, respectively. If these probabilities stay within the confidence band $[\alpha\%, 1-\alpha\%]$, with $\alpha\%$ taking the usual 1% or 5% values, then we can conclude that the quality of the data fit good. Otherwise, there may be situations in which the underlying process does not fit the data well. Another graphical tool useful to check the forecasting ability of the calibrated densities is given by the empirical cumulative distribution function of the futures prices $F_Q(p_{T_i})$ and $F_P(p_{T_i})$, respectively. When the estimated densities are the true densities, the PITs are uniform and independent and hence the empirical cumulative distribution function of the PITs should be close to the 45-degree line. Fig. 4 reports the time series plots of the PITs in the case of the risk-neutral and the two parametric and non-parametric methods for the real-world measures as well as their empirical cdfs. All the graphical tools we used suggest that the forecasts provided by both risk-neutral and real-world densities are accurate.

However, formal tests are needed to evaluate the accuracy of density predictions and to establish whether real-world option-implied densities have a superior forecasting power over the risk-neutral ones. Therefore, in conjunction with the graphical analysis, we first test the forecasting ability of the empirical densities calculating the diagnostic statistic of Berkowitz (2001) and then the Amisano and Giacomini (2007) test.

The results of Berkowitz (2001) test are reported in Table 3. The risk-neutral densities as well as the real-world densities provide accurate forecasts of Phelix Futures prices, given that we do not reject the null hypothesis according to which the forecast densities coincide with the true densities generating the electricity futures rates.

[12] When choosing the length of the first window, we faced a trade-off between the reliability of the calibration for the first few windows and the accuracy of the tests used to evaluate the real-world density forecasts. If the first window is too short, one has more real-world density forecasts but the initial ones are less reliable. If instead one increases its length, the initial calibrations are more accurate but there are fewer observations for the tests to assess the accuracy of real-world density forecasts. A length of 12 for the first window seems a good compromise.

[13] Due to higher costs of production technologies and fuel sources (as hydro, nuclear, coal, oil, and natural gas.)



(a) 25 May 2012 (b) 27 June 2014

(c) 24 July 2015 (d) 25 October 2016

Fig. 3. Density Plots for four different calibration dates (25 May 2012, 27 June 2014, 24 July 2015, and 25 October 2016). *Note*: 'RN' stands for Risk-Neutral, 'RW P' denotes the real-world density derived using the parametric method, and 'RW NP' denotes the real-world density derived using the non-parametric method.

The results of the Amisano and Giacomini (2007) test are reported in Table 4 for the three pairs of density forecasts. We detail the results of the tests considering different weighting functions depending on whether the focus is on the center of the distribution, the tails of the distribution, the right tail only or the left tail only.

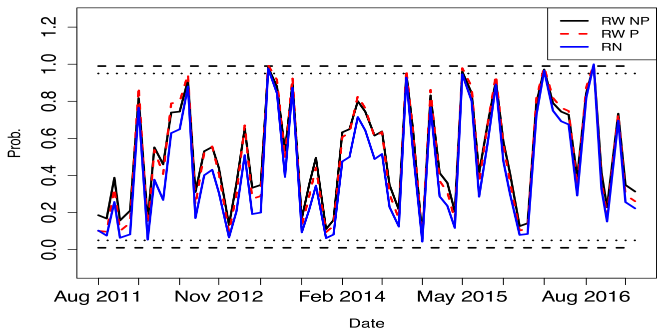
When comparing real-world and risk-neutral densities (Panels B and C), with a focus on the centre of the distribution, the test statistic (3.10) is positive, indicating that the weighted average score is larger for real-world densities, but the superiority in the forecasting performance is not statistically significant. The test statistic is also positive, but insignificant when we compare the two real-world densities (Panel A), given that the p-value is 84%. When forecasting the tails of the distribution, either jointly or separately, the non-parametric method seems to have a superior performance, but again the three *p*-values are large and, hence, the corresponding differences of weighted average scores are not statistically significant.

In a nutshell, both the risk-neutral and real-world densities have good forecasting power for electricity futures prices. In addition, the non-parametric models seem to perform better than parametric models, but the difference in forecasting accuracy between the two methods is not statistically significant.

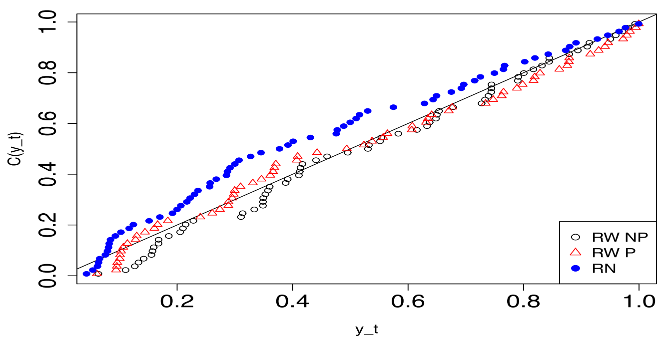
5.3. The pricing kernels

The pricing kernels for the same four trading days associated with Fig. 3 are illustrated in Fig. 5. In the pricing kernel literature, most studies document an S – shape pricing kernel, but this is in contradiction with most asset pricing models.[14] Recently, the U – shape has been reported for pricing kernels extracted from options on stock prices (e.g.

[14] See discussion and review on these issues in Figlewski (2017) and Sichert (2019)



(a) Time Series Plots



(b) QQ Plots

Fig. 4. Backtesting the precision of forecasting the empirical future value of energy futures. *Note*: The dashed lines in (a) represent the 1% and 99% bands, while the dotted lines represent the 5% and 95% bands. 'RN' stands for Risk-Neutral, 'RW P' denotes the real-world density derived using the parametric method, and 'RW NP' denotes the real-world density derived using the non-parametric method. In (b) we plot the empirical cumulative distribution function of the PITs.

Christoffersen et al., 2013; Grith et al., 2013; Sichert, 2019) helping to explain cross-sectional stock return anomalies and the pricing kernel puzzle.

The estimated U-shaped kernels observed in Fig. 5 suggest that the stochastic discount factor is increasing when the market returns are either largely positive or largely negative. Hence, investors in the electricity market regard the states associated with extreme returns on futures prices (values on the tails) as bad states and assign a high value for payoffs received in those states. The U-shaped kernels might be due to the heterogeneous nature of investors in the electricity derivative market. On one hand, investors (such as net long investors) holding net long futures positions, will bear losses when futures prices decrease if their positions are unhedged. They regard negative returns as bad states and highly value payoffs received in these states. On the other hand, investors (such as net short investors) holding net short futures positions, will suffer from increasing futures prices and consider those states with positive returns as bad states. They assign a high value to payoffs received when electricity futures returns are extremely high. The U-shape can also be linked to the variance risk premium and, therefore,

Table 3
Berkowitz Tests Results.

	RN	RW	RW NP
LR_1 Test Stat	2.0625	1.5225	1.5031
LR_1 *p*-value	0.1510	0.2172	0.2202
LR_3 Test Stat	3.7564	2.9319	4.5580
LR_3 p-value	0.2890	0.4022	0.2072

Note: 'RN' stands for Risk-Neutral, 'RW P' denotes the real-world density derived using the parametric method, and 'RW NP' denotes the real-world density derived using the non-parametric method.

Table 4
Results of the testing procedure of Amisano and Giacomini (2007).

	Center	Tails	Right Tail	Left Tail
weight	$w(y)=\varphi(y)$	$w(y)=1-\varphi(y)/\varphi(0)$	$w(y)=\Phi(y)$	$w(y)=1-\Phi(y)$
Panel A: f_1: RW P, f_2: RW NP				
Test Stat	0.2018	−0.3682	−0.1356	−0.1853
p-value	0.8401	0.7127	0.8921	0.8530
Panel B: f_1: RW P, f_2: RN				
Test Stat	0.3039	−0.0839	−0.2909	0.6011
p-value	0.7612	0.9331	0.7711	0.5478
Panel C: f_1: RW NP, f_2: RN				
Test Stat	0.1089	0.3056	−0.0512	0.4335
p-value	0.9133	0.7599	0.9592	0.6647

Note: The tests compare the predictive performance of density forecast f_1 and density forecast f_2 in the centre, both tails, right tail, and left tail of the real-world distribution of $y=\log(p_T/p_t)$. $\varphi(\cdot)$ and $\Phi(\cdot)$ denote the standard normal pdf and cdf, respectively. 'RN' stands for Risk-Neutral, 'RW P' denotes the real-world density derived using the parametric method, and 'RW NP' denotes the real-world density derived using the non-parametric method.

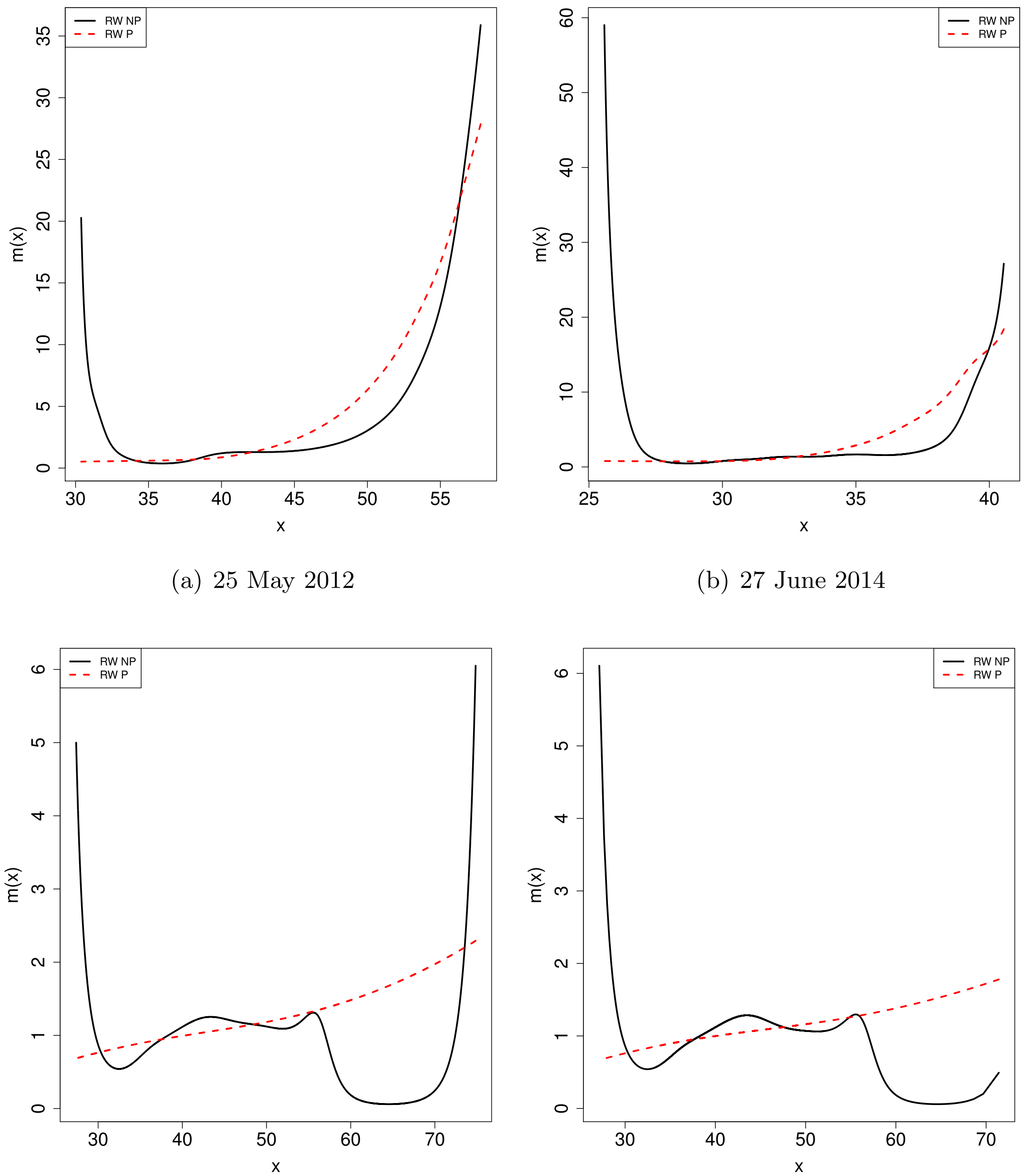
the Heston model may present an advantage over other models applied earlier in the literature to extract the risk-neutral density.

Moreover, we observe that the non-parametric method also produces humps in the pricing kernel, which can be explained by the sudden spikes in electricity markets. However, consistent with the models presented in Bollerslev et al. (2009), Drechsler and Yaron (2010) and Song and Xiu (2016), the parametric pricing kernel has a monotonically increasing shape. The reason can stem from the fact that parametric models often impose restrictions on the data for tractability or computational feasibility, which may not be satisfied by the real data. The monotonically increasing kernel would indicate that investors assign higher state prices to more positive returns.

Table 5 describes the development over time of the pricing kernel. More precisely, we report the pricing kernel, calculated with the parametric ('P') or non-parametric ('NP') method, that corresponds to the αth%-quantile of the risk-neutral distribution. At the same time, we also compute the RND αth%-quantile. There is a clear overall increasing pattern over time for the pricing kernels associated with the first and fifth quantile and with the median of the RND and a decreasing pattern for RND quantiles, the exception being only 2016. Furthermore, we notice an overall decreasing trend for the pricing kernels corresponding to 95% and 99% -quantile of the RND.

Fig. 6 describes the evolution over time of the pricing kernels corresponding to the 5th% and 95th% quantiles of the risk-neutral distribution. The pricing kernels corresponding to the 95% quantile of the risk-neutral distribution of the electricity futures seem to converge eventually in 2016, under both parametric and non-parametric methods. Meanwhile, the pricing kernels corresponding to the 5% quantile seem to differ more or less by the same amount. It is of importance to explore if this difference has any significant impact on the actual values of the risk premia calculated under the parametric and non-parametric methods.

Table 5 and Fig. 6 show that the derived pricing kernels are the greatest for large values of the Phelix Base Future. Hence, market participants assign higher state prices to those payoffs in states with higher future electricity prices than the expected ones. Thus, investors are more risk-averse to high electricity prices. This is in line with evidences in interest market found by Ivanova and Gutiàrez (2014). It is also clear that the parametric method gives larger values of the pricing kernel for quantiles of the RND not too deep in the tails. For more extreme quantiles of the RND, the non-parametric method provides larger pricing kernels. Finally, the pricing kernels corresponding to quantiles in the right tails (99% and 99.5%), calculated with both methods, seem to peak during 2012.



(a) 25 May 2012

(b) 27 June 2014

(c) 24 July 2015

(d) 25 October 2016

Fig. 5. Pricing kernels for four different calibration dates (25 May 2012, 27 June 2014, 24 July 2015, and 25 October 2016). *Note*: 'RW P' denotes the real-world density derived using the parametric method, and 'RW NP' denotes the real-world density derived using the non-parametric method.

5.4. Risk premia

Ultimately for investors, the risk premium is the quantity of most interest. The methodology used in this paper is flexible enough to allow a direct computation of risk premium in the EEX electricity market. The time series plot of risk premia is illustrated in Fig. 7 and their descriptive statistics are reported in Table 6. The time series values are available in the Appendix (Table A.1).

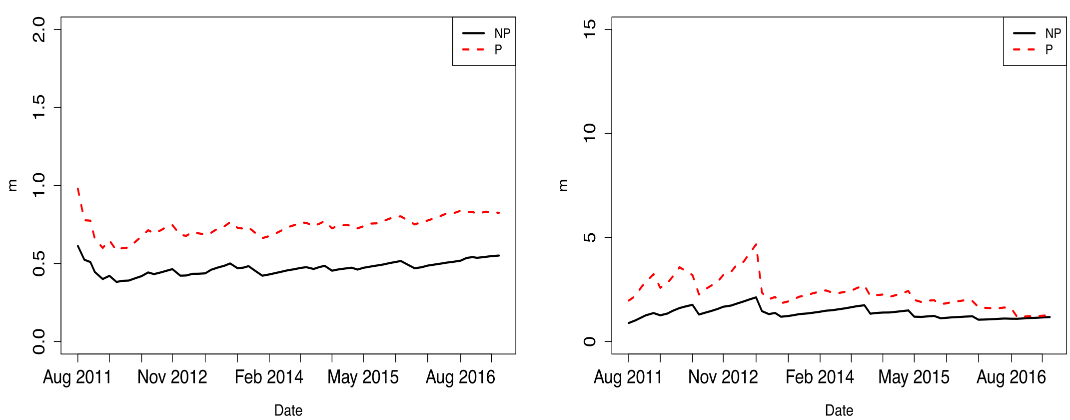
Our calculations suggest that the computed risk premia are negative and remarkably similar under the parametric and non-parametric methods. The results we obtained are in accordance with the theoretical model of Bessembinder and Lemmon (2002) extended to options written on futures. Moreover, similar risk premia behaviour has been recently observed in interest rate markets by Ivanova and Gutiàrez (2014), who estimated a negative market price of risk based on information extracted from Euribor futures options and on both parametric and non-parametric methods.

The findings for Phelix electricity market differ from other asset classes. In the equity markets, the general evidence supports positive values for the risk premia (Broadie et al., 2007; Santa-Clara and Yan, 2010; Bollerslev and Todorov, 2011). Analysing currency options markets, Jurek and Xu (2014) identified positive currency risk premia and further showed that the option-implied currency risk premia generated an unbiased forecast of monthly currency excess returns. For many commodity markets, positive values are reported for the forward risk premia in Moosa and Al-Loughani (1994); whilst Considine and Larson (2001) and Bolinger et al. (2006) found non-negative commodities risk premia for natural gas and crude oil. In contrast with the findings by Bessembinder and Lemmon (2002) in the electricity market, Chevallier (2010) documented a positive time-varying risk premia

Table 5
Evolution of the pricing kernels over time.

	Year	2011	2012	2013	2014	2015	2016	2017
Q(1)	P	0.5154	0.6922	0.6265	0.6990	0.7639	0.7468	0.7463
	NP	0.3369	0.6904	0.9082	1.1037	1.4838	1.4517	1.5686
	RND q.	44.0771	41.5809	36.2160	31.6123	23.3142	27.4831	23.6519
Q(5)	P	0.5999	0.6839	0.6903	0.7253	0.7739	0.8322	0.8250
	NP	0.4004	0.4221	0.4473	0.4540	0.4905	0.5429	0.5510
	RND q.	46.8088	43.8008	38.2392	33.9646	25.3657	30.5235	25.8419
Q(50)	P	0.9927	0.9327	0.9708	0.9500	0.9462	1.0078	1.0008
	NP	1.3878	1.1696	1.2671	1.0974	1.1287	1.1931	1.2049
	RND q.	54.1696	49.0361	42.9207	38.6831	29.2240	38.8170	30.8846
Q(95)	P	3.2404	3.3550	2.2294	2.2589	1.9449	1.2142	1.2666
	NP	1.3698	1.7310	1.3506	1.3934	1.1801	1.1422	1.1762
	RND q.	62.7767	55.0998	48.2975	44.4031	33.8070	48.6402	36.7632
Q(99)	P	7.1654	8.2823	3.9037	4.1161	3.2181	1.3466	1.4572
	NP	1.8911	6.7811	1.3451	1.6253	1.6842	1.2852	1.3425
	RND q.	66.7617	58.2330	51.1099	48.0160	36.9317	53.2395	40.0372

Note: The table presents the pricing kernels for the last available month of each year. The block denoted by '$Q(\alpha)$' reports the pricing kernel, calculated with the parametric ('P') or non-parametric ('NP') method, that corresponds to the αth%-quantile of the risk-neutral distribution and the RND α%-quantile, reported in the last row of each block.



(a) 5% quantile (b) 95% quantile

Fig. 6. Pricing kernels corresponding to the 5%, and 95%- quantiles of the risk-neutral distribution. *Note*: 'P' denotes the pricing kernel calculated with the parametric and 'NP' the one calculated with the non-parametric method.

and a positive relationship between risk premia and skewness of CO_2 spot prices. Expanding the research in a different direction with a model-independent approach, Trolle and Schwartz (2010) found evidence that the average variance risk premium for crude oil and natural gas was negative. This is similar to equity markets where Bollerslev et al. (2011) provided evidence of mostly negative volatility risk premia.

Cox et al. (1985) showed that the market price of risk equals the covariance of changes in the future underlying price with percentage changes in the investor's wealth. Hence, the negative covariance that we document implies that high future electricity prices are associated

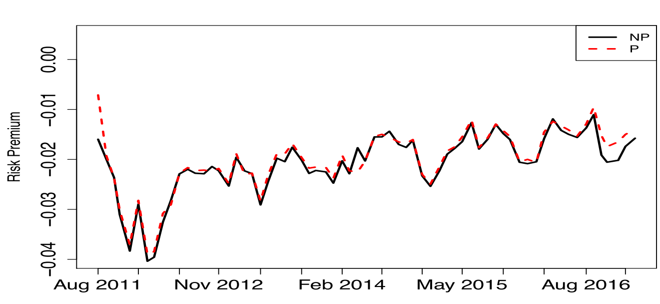


Fig. 7. The time-series of estimated risk premia for the EEX Phelix electricity futures prices. *Note*: 'P' denotes the risk premia calculated with the parametric and 'NP' the one calculated with the non-parametric method.

Table 6
Descriptive statistics for the calculated risk premia for the EEX Phelix electricity futures prices.

	P	NP
Min.	−0.0390	−0.0404
st Qu.	−0.0226	−0.0228
Median	−0.0193	−0.0203
Mean	−0.0200	−0.0208
rd Qu.	−0.0154	−0.0161
Max.	−0.0071	−0.0110
Std. Dev.	0.0062	0.0061

Note: 'P' denotes the risk premia calculated with the parametric and 'NP' the one calculated with the non-parametric method.

with low wealth and ultimately with an economic downturn. The results are, therefore, in line with the previous findings asserting that pricing kernels are larger in states with high future electricity prices, and hence, confirming their perception by the market as a negative outlook for the economy.

There is an observable seasonality in the risk premia, which should be expected given that the underlying asset under study is energy related, but there is also an upward trend between 2011 and 2016. These findings are consistent with those of Lucia and Torró (2011) and Bevin-McCrimmon et al. (2018).

Electricity option prices contain rich information including the market participants' perceptions of the probability distribution of the underlying asset. Our empirical results reveal that these probability densities are positively skewed, therefore electricity prices and volatility are positively correlated. Furthermore, the volatility responds asymmetrically to the information flow as positive shocks on electricity returns enhance the volatility more than negative shocks. This suggests that the electricity option market corrects itself by incorporating the higher probability of a future upsurge in electricity prices in the option premium. Both risk-neutral and real-world densities can be used to forecast well the Phelix futures prices. The time-varying pricing kernel shows a U-shaped behaviour, meaning that the stochastic discount factor increases when the market returns are either extremely high or low. This result highlights a heterogeneous nature of investors within the electricity market and a higher risk aversion to heightened prices. Finally, we find that electricity risk premia are negative, corroborating the fact that expected Phelix futures prices are lower than prices inferred from current option prices.

6. Conclusions

Over the last decades electricity markets have been transformed from highly regulated systems into deregulated markets. Concurrently, trading in electricity derivatives has surged significantly despite the very unique nature of its underlying (electricity), which in contrast to other commodities, cannot be stored. The present study examines option prices written on electricity futures traded on the European Energy Exchange with the purpose of recovering the probability density functions and derive the informational content of electricity derivatives useful to gauge any shifts in the market's expectations. This study is one of the very few studies on this particular set-up.

Using a recent dataset covering six years of Phelix Options prices, we extract the risk-neutral probability density functions from these options prices assuming the stochastic volatility model of Heston (1993) for the underlying futures price. Then, we apply both parametric and non-parametric statistical calibration methods to convert the risk-neutral densities into the real-world counterparts.

The descriptive statistics regarding the options underlying assets indicate that electricity spot prices are more volatile and display more frequent spikes than futures prices. This feature is in line with the analyses by Bessembinder and Lemmon (2002) and Knittel and Roberts (2005). Indeed, electricity spot markets exhibit very high volatility because supply and/or demand shocks cannot be smoothed out with inventories, since these are no physically possible.

The core results of our analysis reveal that real-world and risk-neutral option-implied densities provide an accurate forecast of Phelix futures prices. In particular, real-world densities are able to get closer to the QQ plot 45-degree line than risk-neutral densities, which supports a slightly superior forecasting ability of the real-world distributions. The significant explanatory power about future levels of electricity futures prices, extracted from option prices, may be attractive to the class of speculative investors who may like to take advantage from this particular energy market. Furthermore, it can be useful for market participants, utility companies, large industrial consumers that will be able to forecast the volatile electricity prices with a reasonable level of accuracy and thus adjust their bidding strategy and their own production or consumption schedule in order to reduce risks or maximise their profits in day-ahead trading.

Our study further documents that the examined electricity densities are positively skewed. This points to an inverse leverage effect in electricity derivatives markets and would indicate higher aversion for increasing prices. Hence, market participants fear a positive shock to electricity price more than an equally large price drop because of the negative effect that an extreme price rise would have on the real economy. While the equity markets are characterized by lower prices and higher volatility, with a negative correlation between equity returns and volatility, the electricity market, similarly to other energy markets, displays a positive correlation between price-returns and volatility.

We estimate a U-shaped pricing kernel for Phelix electricity, that also exhibits humps from time to time. The U-shape seems more accentuated in the right tail, suggesting that the (stochastic) discount factor is increasing when the market return is positive. This is in line with recent research on pricing kernel reconstruction from option prices. The U-shape of the pricing kernel could be due to the heterogeneous nature of investors in the electricity derivatives market and to the variance risk premium. Therefore, the stochastic volatility Heston model may offer a good solution to the reconstruction of the risk-neutral density of electricity prices. In addition, we bring evidence of negative risk premia with seasonal patterns and conclude that in the power derivatives market investors require higher compensation in states of high electricity prices. This result is likely due to the special characteristics of electricity. The insights provided in our study may help regulators and other decision makers better understand the behaviour of market participants in a highly competitive market. Furthermore, the extraction of both risk-neutral and real-world densities of electricity futures allows direct computational solutions for pricing more advanced financial products, in the case of the former, and for deriving risk measures such as value-at-risk and expected shortfall, for the latter, which we leave for future research.

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Appendix A. Risk premia

Table A.1
Evolution of the calculated risk premia.

Date	P	NP	Date	P	NP	Date	P	NP
26/08/2011	−0.0071	−0.0160	26/07/2013	−0.0189	−0.0204	26/06/2015	−0.0121	−0.0126
26/09/2011	−0.0193	−0.0200	23/08/2013	−0.0168	−0.0176	24/07/2015	−0.0176	−0.0179
25/10/2011	−0.0237	−0.0236	27/09/2013	−0.0196	−0.0201	25/08/2015	−0.0157	−0.0160
15/11/2011	−0.0302	−0.0310	25/10/2013	−0.0217	−0.0228	25/09/2015	−0.0129	−0.0130

(continued on next page)

Table A.1 (*continued*)

Date	P	NP	Date	P	NP	Date	P	NP
23/12/2011	−0.0371	−0.0383	19/11/2013	−0.0215	−0.0222	23/10/2015	−0.0142	−0.0148
24/01/2012	−0.0282	−0.0289	27/12/2013	−0.0216	−0.0225	17/11/2015	−0.0154	−0.0160
27/02/2012	−0.0390	−0.0404	24/01/2014	−0.0238	−0.0247	23/12/2015	−0.0205	−0.0206
23/03/2012	−0.0384	−0.0396	26/02/2014	−0.0191	−0.0203	22/01/2016	−0.0200	−0.0208
25/04/2012	−0.0308	−0.0325	25/03/2014	−0.0223	−0.0229	24/02/2016	−0.0206	−0.0205
25/05/2012	−0.0291	−0.0282	25/04/2014	−0.0225	−0.0177	24/03/2016	−0.0145	−0.0159
26/06/2012	−0.0228	−0.0229	23/05/2014	−0.0203	−0.0203	26/04/2016	−0.0124	−0.0119
27/07/2012	−0.0216	−0.0220	27/06/2014	−0.0154	−0.0155	27/05/2016	−0.0133	−0.0142
24/08/2012	−0.0222	−0.0228	25/07/2014	−0.0150	−0.0155	24/06/2016	−0.0141	−0.0150
26/09/2012	−0.0221	−0.0229	22/08/2014	−0.0155	−0.0144	26/07/2016	−0.0153	−0.0156
26/10/2012	−0.0223	−0.0214	26/09/2014	−0.0165	−0.0170	29/08/2016	−0.0129	−0.0137
20/11/2012	−0.0218	−0.0223	24/10/2014	−0.0168	−0.0176	26/09/2016	−0.0096	−0.0110
28/12/2012	−0.0249	−0.0253	18/11/2014	−0.0160	−0.0162	25/10/2016	−0.0152	−0.0191
25/01/2013	−0.0189	−0.0196	23/12/2014	−0.0230	−0.0233	15/11/2016	−0.0174	−0.0205
25/02/2013	−0.0230	−0.0223	23/01/2015	−0.0249	−0.0254	27/12/2016	−0.0165	−0.0202
25/03/2013	−0.0228	−0.0228	26/02/2015	−0.0214	−0.0222	23/01/2017	−0.0150	−0.0174
26/04/2013	−0.0283	−0.0291	27/03/2015	−0.0183	−0.0189	28/02/2017	−0.0139	−0.0158
24/05/2013	−0.0232	−0.0245	24/04/2015	−0.0175	−0.0178			
26/06/2013	−0.0189	−0.0198	22/05/2015	−0.0155	−0.0164			

Note: 'P' denotes the risk premia calculated with the parametric method and 'NP' the one calculated with the non-parametric method.

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