Energy Economics 40 (2013) 976–988

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneco

A model for hedging load and price risk in the Texas electricity market

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ARTICLE INFO

Article history:
Received 10 August 2012
Received in revised form 10 May 2013
Accepted 20 May 2013
Available online 15 June 2013

JEL classification:
C60
C80
G12
G13
Q40

Keywords:
Electricity market
Structural model
Spikes
Forward prices
Spread options
Hedging

ABSTRACT

Energy companies with commitments to meet customers' daily electricity demands face the problem of hedging load and price risk. We propose a joint model for load and price dynamics, which is motivated by the goal of facilitating optimal hedging decisions, while also intuitively capturing the key features of the electricity market. Driven by three stochastic factors including the load process, our power price model allows for the calculation of closed-form pricing formulas for forwards and some options, products often used for hedging purposes. Making use of these results, we illustrate in a simple example the hedging benefit of these instruments, while also evaluating the performance of the model when fitted to the Texas electricity market.

1. Introduction

In recent years, the use of financial products, such as futures and options, by retail suppliers to hedge electricity price and demand spikes has grown. The occurrence of spikes in electricity markets, as well as their relationship to loads (energy demands) which have strong seasonal components, requires non-standard financial models. On the other hand, having continuous-time stochastic models built around Brownian motion, as is typical for understanding options in financial markets, allows for convenient pricing formulas which can reduce the simulation burden on an optimization program for hedging risk.

The model we propose aims to capture the unique features and complex dependence structure of electricity price and load dynamics while retaining enough mathematical tractability to allow for such pricing results. In particular, we include as state variables the key factors which drive electricity prices, such as fuel price (natural gas in particular), load itself, and a proxy for capacity available. We express power spot price as a parametric function of underlying factors, including an additional 'regime' to describe the risk of extreme price spikes, which are most likely to occur when demand is relatively high, for example during times of unexpectedly high temperatures. We also model periodicity and seasonality in load and price at various time horizons to reflect hourly patterns, weekends, and also annual effects. Despite the rich dependence structure embedded in the model, convenient formulas for derivative prices are available, facilitating the calibration to market data and the model's application to hedging problems.

We choose to analyze data from the US electricity market in Texas, often referred to as ERCOT (Electric Reliability Council of Texas), after the name of the ISO (Independent System Operator) which manages the Texas Interconnection power grid. Along with the Eastern and Western Interconnections, it is one of the three main electricity grids in the US and serves over 20 million customers. As in many electricity markets around the world, deregulation in Texas occurred approximately ten years ago. Since then, the highly volatile and quite dramatic behavior of prices has drawn much attention to the challenges of electricity price modeling. Given the growth of intermittent wind energy in Texas and the state's susceptibility to heat waves and other extreme weather, features such as price spikes are particularly important for the ERCOT market. A strong reminder of this was provided by the heat wave of early August 2011, when the total load hit a record level of 68.4 GWh, and day-ahead prices for peak afternoon hours reached their cap of $3000 per MWh on several consecutive days. Such extreme events may be even more dramatic in the future, following a recent decision by ERCOT to increase the cap

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0140-9883/$ – see front matter
http://dx.doi.org/10.1016/j.eneco.2013.05.020

to $4500 effective August 2012 and to increase it to as high as $9000 by 2015.

Much of the literature on quantitative models for electricity prices has focused on extending traditional finance approaches to account for these spikes, for example through jump processes. Such approaches typically begin by specifying a stochastic process directly for the electricity spot price, possibly incorporating several unobservable factors, seasonal functions and sometimes multiple regimes (typically lasting just a few hours, so one should not interpret the terminology 'regime' to mean a lasting paradigm shift). An early single-factor model by Cartea and Figueroa (2005) uses a jump diffusion process, while Hambly et al. (2009) separates the jumps from the diffusion in a two-factor version to account for very rapid recoveries from price spikes. In Geman and Roncoroni (2006), the authors instead propose a threshold level above which jumps become negative to recover from spikes, while several authors (cf, De Jong and Huisman, 2003; Weron et al., 2004) have instead suggested regime-switching models to handle sudden spikes and rapid recoveries. In Benth et al., a general framework based on sums of Lévy processes is advocated, which can allow for some convenient results for forward prices, while in Veraart and Veraart (2012) the authors apply multivariate Lévy semistationary processes to the EEX market in Europe. Another alternative is the use of heavy-tailed distributions such as the Cauchy distribution, as presented in Kim and Powell (2011) and applied to two US markets, PJM and ERCOT.

While the above works differ extensively in both their motivations and mathematical details, they all share the characteristic of taking spot electricity prices as the starting point for a stochastic model, thus placing them in the category of 'reduced-form' models. While such approaches may be successful for capturing price spikes and overall price distributions, they rarely capture the complicated dependence structure between price, load and other factors, which is equally vital for hedging purposes in practice. Hence, we instead favor the category often known as 'structural' models, as reviewed for example in the recent survey paper of Carmona and Coulon (2013). In such a model, power price is written as a function of several underlying supply and demand factors, and its dynamics are therefore not specified directly through an SDE (stochastic differential equation), but produced indirectly as a result of the dynamics chosen for the factors. Early work by Barlow (2002) treated demand as the only driving factor, before various authors extended this branch of the literature to include factors such as fuel prices (Carmona et al., 2013; Pirrong and Jermakyan, 2008), capacity changes (Burger et al., 2004; Cartea and Villaplana, 2008), or both (Aïd et al., 2013; Coulon and Howison, 2009).

A benefit of the structural approach is that it makes use of readily available information on fundamentals such as market load and in some cases supply side information like generation costs. However, for mathematical tractability, it stops short of a full description of all the details of the price setting mechanism such as operational and transmission constraints, instead simply approximating the shape of the electricity stack. Nonetheless, it reflects key features of load and price dynamics, such as the observation that times of high load are more likely to produce price spikes, for example when the highest cost and least efficient units are forced to run to satisfy demand. This close relationship between load and price is important for energy companies to understand when hedging the risk of either physical asset ownership or their obligations to serve retail customers at predetermined price levels. However, the relationship between price and load is blurred by effects such as outages, transmission problems and other constraints or shocks which can sometimes produce price spikes even at periods of low or average demand. Such complications of the electricity grid create a challenge for structural models that rely on a clear and consistent relationship between price and load. Adding additional unobservable factors such as jump processes is a common reduced-form solution to such obstacles, but less in the spirit of the structural approach.

We therefore propose a model which builds on the structural approaches mentioned above, but also incorporates some ideas from the reduced-form literature in order to obtain a better fit to the ERCOT market. In particular, we extend the typical stack-based methodology (e.g., as in Aïd et al., 2009; Coulon and Howison, 2009; Pirrong and Jermakyan, 2008) to include a 'spike regime', in which the price-to-load relationship adjusts to reflect such times of extreme market conditions. Within each regime, the power price is lognormal, but we show that the mixing of these lognormals can produce the heavy-tailed price densities observed in the market. The probability of being in the spike regime is also assumed to be load-dependent, yet we retain the important advantage of closed-form solutions for forward and option prices, exploiting convenient properties of multivariate Gaussian distributions. Section 2 introduces the model, while Section 3 presents the results for forwards, as well as parameter estimation and calibration. In Section 4, we present the related closed-form option pricing results and then in Section 5 study an application of the model to hedging an obligation to serve customer load. Finally we conclude in Section 6.

2. Model and motivation

The electricity price model consists of several separate pieces, corresponding to each of the underlying stochastic factors followed by their link with spot power price. In this section, we address each of these in turn, and introduce the parameters and notation.

2.1. Load

The primary short-term driver for electricity prices is load, which is the starting point of our analysis. Later we will incorporate the longer-term effects of fuel prices, specifically through natural gas prices.

Fig. 1a shows the striking seasonal variation in daily average load. In fact as Fig. 2 shows, the seasonal pattern varies significantly hour to hour throughout the day. For example, hour 8 has both a summer and a winter peak, while hour 16 only has a summer peak and a much greater peak to trough ratio. There are also periodicities caused by weekends when businesses are closed.

We first de-seasonalize the ERCOT load L_t:

$$L_t = S(t) + \overline{L}_t,$$

where the seasonal component (estimated using hourly data) is given by

$$S(t) = a_1(h) + a_2(h)\cos(2\pi t + a_3(h)) + a_4(h)\cos(4\pi t + a_5(h)) + a_6(h)t + a_7(h)1_{we}.$$

Here h is the hour, and 1_{we} is an indicator variable for weekends; a_2 to a_5 are the seasonal components, a_6 picks up the upward trend visible in Fig. 1a, and a_7 captures the drop in demand on weekends. Fig. 2 shows the fitted seasonal components for hours 8 and 16.

Then we fit the residual load $\overline{L}_t$ to an Ornstein–Uhlenbeck (OU) model:

$$d\overline{L}_t = -\kappa_L \overline{L}_t\, dt + \eta_L dW_t^{(L)}.$$

2.2. Structural electricity model

From Fig. 1b, we observe that electricity prices exhibit high volatility and numerous spikes, and they seem to fluctuate around a level driven by natural gas prices. We use the well-known one-factor