Energy Economics 59 (2016) 423–434

Contents lists available at ScienceDirect

Energy Economics

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

Parametric model risk and power plant valuation ☆

Karl Bannör[a], Rüdiger Kiesel[b,*], Anna Nazarova[b], Matthias Scherer[a]

[a] Chair of Mathematical Finance, Technische Universität München, Parkring 11, Garching-Hochbrück 85748, Germany
[b] Chair for Energy Trading and Finance, University of Duisburg-Essen, Campus Essen, Universitätsstraße 12, Essen 45141, Germany

ARTICLE INFO

Article history:
Received 25 March 2015
Received in revised form 4 August 2016
Accepted 13 August 2016
Available online 1 September 2016

JEL classification:
G13
Q40
C10
C40

Keywords:
Power plant valuation
Parametric model risk
Spikes
Energy markets
Spark spread option

ABSTRACT

The fact that model and parameter risk are important sources of uncertainty in option pricing models and for risk management procedures has recently been recognised for financial markets, see Cont (2006); Morini (2011); Bannör and Scherer (2013). In the context of energy markets, investment decisions are often based on the valuation of fossil power plants as real options — depending on various underlying processes such as the power-, carbon emission certificate-, and gas price. To capture parametric model risk inherent in the valuation procedure of fossil power plants, we use a methodology recently established in Bannör and Scherer (2013). As gas-fired power plants are seen as flexible and low-carbon sources of electricity, which are important building blocks in terms of the switch to a low-carbon energy generation, we consider the model risk in this asset class in detail. Our findings reveal that spike risk is by far the most important source of parametric model risk.

1. Introduction and motivation

Ever since the financial crisis struck the importance of models has been in the centre of attention. In particular, it has been realised that risk management is subject to model risk and that model risk has to be adequately measured. Energy markets are substantially exposed to parameter risk, or even ambiguity between different possible models, as the underlying processes are driven by diffusion and jump components resulting in a parameter space of considerable dimension. In some cases, one might be able to assign probabilities to the different models (resp. parameters within a specific model). Such probabilities might be interpreted as a measure of trustworthiness that we assign to specific parameters. In the terminology of Knight (1921), this corresponds to a situation with parametric model risk, and obviously it is related to a Bayesian perspective on the topic.

For standard financial markets the issue has been addressed extensively in recent years. For instance, Avellaneda et al. (1995) and Cont (2006) consider worst-case scenarios and obtain a range of possible prices for derivatives. Rebonato (2010) addresses model risk issues concerning stress testing, while Glasserman and Xu (2014) and Kiesel et al. (2014) discuss robust approaches to risk management including model risk.

On the regulatory side the issue has been addressed by the Basel Committee, BIS (2009) and the US Federal Reserve, FED (2011), which actually states: "An understanding of model uncertainty and inaccuracy and a demonstration that the bank is accounting for them appropriately are important outcomes of effective model development, implementation, and use". In this context our approach delivers a tool to perform an appropriate assessment of model risk. The US Federal Reserve, FED (2014), also comments on the practical implementation suggesting data handling and estimation in a similar way as we follow below. Morini (2011) provides an overview of regulatory requirements and practical implementations concerning model risk for various financial markets.

☆ The authors thank Björn Fischbach for his valuable research support.
* Corresponding author.
E-mail addresses: bannoer@tum.de (K. Bannör), ruediger.kiesel@uni-due.de (R. Kiesel), anna.nazarova@uni-due.de (A. Nazarova), scherer@tum.de (M. Scherer).
URLs: http://www.mathfinance.ma.tum.de/en/staff/karl-friedrich-bannoer/, http://www.lef.wiwi.uni-due.de/team/ruediger-kiesel/, http://www.lef.wiwi.uni-due.de/team/anna-nazarova/, http://www.mathfinance.ma.tum.de/en/staff/prof-dr-matthias-scherer/ (M. Scherer).

http://dx.doi.org/10.1016/j.eneco.2016.08.004
0140-9883/

In contrast, model risk has not been discussed in the context of energy markets. Given that many structured and derivative contracts cannot be marked to markets (due to limited liquidity), but have to be marked to models, an assessment of potential model risk is particularly important. In view of the recent changes in European energy markets, especially the German “Energiewende”, with the increasing impact of remittent renewable energies, it is evident that models need to be adjusted to changing market conditions. One important aspect is the need for capacity decisions (replacements, new investments, and closures) in the power plant park on a company, national, or even a European level. The financial streams of such an investment can be generated on the market for energy derivatives in terms of spread options. The specific application we consider is the valuation of a gas-fired power plant via option pricing techniques.[1] Flexible gas-fired power plants[2] have been built to address the need in peak hours during the day. So their use is based on short-term demand, which is highly affected by the uncertain feed-in of energy generated by solar or wind power plants. Lambertz et al. (2012) discuss the effect of remittent energy sources on the German electricity market in detail and provide case studies showing particularly volatile days. Gas-fired power plants can be represented as a clean crack spread option, where the owner of such an option is long electricity and short gas and emission certificates. A positive investment decision is made in case such a contract is in the money, meaning that we observe a positive spread on the time interval under consideration. Clearly, such a valuation depends on many risk factors and the stochastic model leading to the price of the power plant is highly non-trivial. We investigate the parametric model risk within a given well established modelling approach (see Section 3.2 for details). Our focus is on identifying the parameters which have the highest impact in case they are mis-specified. Thus we do not provide a horse race between competing models (such an analysis has been done in Benth et al. (2012)), but analyse the sources of parametric model risk within a given model.

The present paper is organised as follows. In the next section we review the methodology introduced by Bannör and Scherer (2013) which we use to access model risk. In Section 3 we explain our stochastic models for the relevant price processes. In Section 4 we undertake our empirical investigation, which consists of fitting appropriate stochastic models to the various price processes, outlining the valuation procedure for power plants in terms of spread options and the calculation of the relevant risk measures according to techniques introduced. In Section 5 we apply these techniques to analyse the parametric model risk of a gas-fired power plant. Section 6 provides a summary and an outlook.

2. Incorporating parameter risk

Modelling electricity prices is a considerable task as the electricity market is still developing and subject to changes in regulation and market design. Nevertheless, there are numerous attempts trying to explain and model the dynamics of electricity prices. For discussions on the use of a regime-switching approach see De Jong (2006). Meyer-Brandis and Tankov (2008) propose a Lévy process setting, which was empirically investigated and compared to competing approaches in Benth et al. (2012).

Carmona et al. (2012) use a structural approach in which prices are generated with an equilibrium approach. Textbook accounts of modelling approaches can be found in Eydeland and Wolyniec (2002) or Burger et al. (2014). After choosing a specific model, one still has to determine the model's correct parameters. In electricity markets, one typically relies on time series analysis to obtain a model's parameters due to the lack of liquid derivative prices to calibrate to. Thus, the standard procedure is to estimate the parameters from time series of electricity prices and to plug the point estimate into the desired calculations afterwards, e.g. the calculation of electricity derivative prices. But, when simply plugging in the obtained parameter for price determination, one disregards the whole information which is contained in the distribution of the estimator. If a parameter may be difficult to estimate (like, e.g., in presence of a small sample size), one faces tremendous risk that one does not obtain the right parameter due to the estimator's bias and/or variance. This risk is not neglectable: when calculating derivative prices, taking a slightly different parameter than the right one may result in considerably different prices (as demonstrated in Schoutens et al. (2004)).

Following the terminology of Knight (1921), the above problem is described as *parameter risk*: via the estimator's distribution one has an idea about the likelihood of the different parameters, but one does not know for sure whether the point estimate parameter is the right one. To account for this, Bannör and Scherer (2013) introduce the framework of parameter risk-captured pricing. This generalises several ideas on treating parameter risk or uncertainty suggested in Cont (2006), Gupta et al. (2010), Lindström (2010) and provides a concise framework to incorporate parameter and estimation risks into financial prices. This framework is discussed in Section 2.1 below.

2.1. Measuring parameter risk and risk-captured prices

The methodology to measure parameter risk in the present context is based on convex risk measures. The notion of convex (and coherent) risk measures[3] has emerged from the shortcomings of the Value-at-Risk. The Value-at-Risk, being some upper quantile, is popular among practitioners and convenient to interpret, but there are settings where the diversification of financial instruments is penalized, i.e. a diversified portfolio of financial positions is regarded more risky than the single positions. To overcome this unrealistic property, alternatives, most notably convex risk measures, have been developed.[4]

When speaking about “*parameter risk*”, we have a distribution R on the parameter space Θ available that quantifies the likelihood/ trustworthiness of the different parameters.[5] This allows us to define the “*risk-captured price*” of some derivative X as a convex risk measure — evaluated on the derivative price regarded as a function of the unknown parameter θ. The idea is intuitive: (i) each parameter $\theta \in \Theta$ implies some derivative price $\theta \mapsto \mathbb{E}_\theta[X]$— but we are ambiguous which parameter to trust. (ii) To reduce this resulting price distribution (implied by the distribution R on Θ) to a number that is easy to interpret, we apply a convex risk measure ρ to $\theta \mapsto \mathbb{E}_\theta[X]$. Note the difference to the standard approach in calculating risk numbers. We apply risk measures to functionals on the underlying parameter space and calculate price intervals according to the significance levels of the risk measure. This addresses the risk implied by the parameter variations (and not the risk implied by price variations as in market risk calculations).

A formal definition of this procedure is given in Definition 1, an illustration is provided in Fig. 1.

[1] The optimal dispatch of thermal power plants under robustness considerations has recently been addressed in Aïd et al. (2016) and Cartea et al. (2016).

[2] According to Lambertz et al. (2012), p. 20, modern power plants are able to change the load by 3 percentage points per minute.

[3] See the seminal paper Artzner et al. (1999).

[4] Convex risk measures have been treated and extended in many papers, see Kusuoka (2001), Föllmer and Schied (2002), Frittelli and Scandolo (2006), and there are numerous tractable examples for convex risk measures available like, e.g., the Average-Value-at-Risk, cf. Acerbi and Tasche (2002).

[5] The distribution R on Θ may be induced, e.g., by an estimator $\hat{\theta} = \hat{\theta}(X_1, \ldots, X_N)$ via the pushforward measure. Alternatively, it might be the result of expert judgement, a calibration, etc.