Model Risk for Energy Markets

Rüdiger Kiesel, Karl Bannör, Anna Nazarova, Matthias Scherer

R. Kiesel | Centre of Mathematics for Applications, Oslo University | Chair for Energy Trading, University of Duisburg-Essen

Motivation

- Model risk has been recognized as one of the fundamental reasons for financial distress for banks and insurance companies. Recently, a number of authors addressed this issue:
  - Schoutens et. al. (2004): A perfect calibration - now what?
  - Cont (2006): Model uncertainty and its impact on the pricing of derivative instruments.
  - Bannör, Scherer (2011): Quantifying the degree of parameter uncertainty in complex stochastic models
- Important questions:
  - How sensitive is the value of a given derivative to the choice of the pricing model (parametric setting)?
  - Can one quantify a provision for model risk (as for market and credit risk)?

Problem Setting

- Model risk has not been discussed in the context of energy markets (to our knowledge).
- A topical question is the need for reinvestment (replacement investments and building more capacity) in the power plant park. The financial streams of such an investment can be generated on the market for energy derivatives in terms of spread options.
- We use the Bannör, Scherer (2011) approach to discuss the model risk in such a valuation problem.

Spread Options

Market participants are exposed to the difference of commodity prices. Examples are

- the dark spread between power and coal (model for a coal-fired power plant)
- the spark spread between power and gas (model for a gas-fired power plant)
- In countries covered by the European Union Emissions Trading Scheme, utilities have to consider also the cost of carbon dioxide emission allowances. Emission trading has started in the EU in January 2005.

Clean Spark Spread

$$CSS_\tau = P_\tau - h\, G_\tau - c_E\, E_\tau, \tag{1}$$

where P_τ is the power price, G_τ is the gas price, E_τ is the carbon certificate price at maturity τ, h is the heat rate, c_E emission conversion rate.

- The clean spark spread reflects the profit/loss of generating power from gas after taking into account gas and carbon allowance costs.
- A positive spread effectively means that it is profitable to generate electricity, while a negative spread means that generation would be a loss-making activity.
- Note that the clean spark spreads do not take into account additional generating charges beyond gas and carbon.

Present Value of a Power Plant

- The operator acts on the spot market. The specific daily configuration of the power plant is not traded, so we use historical probabilities.
- We don't consider any further restrictions.
- The plant runs for another few years, so future values will be discounted.

Spread Options to Manage Market Risk

- Spread options can be used by owners of corresponding plants to manage the market risk. Instead of spread trading with futures the owner of a power plant can directly purchase/sell a spread option.
- The payoff of a typical spread option is

$$C_{\text{spread}}^{(\tau)} = \max(S_1(\tau) - S_2(\tau) - K, 0)$$

with S_i the underlyings, K the strike.

Valuation of Spread Options

In the Black Scholes world there is an analytic formula for $K = 0$ (exchange option) due to Margrabe (1978).

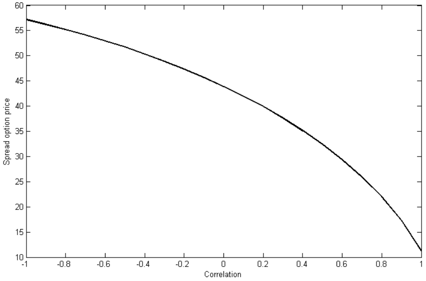
$$
\begin{aligned}
C_{\text{spread}}(t) &= (S_1(t)\Phi(d_1) - S_2(t)\Phi(d_2)) \\
P_{\text{spread}}(t) &= (S_2(t)\Phi(-d_2) - S_1(t)\Phi(-d_1)) \\
\text{where} \quad d_1 &= \frac{\log(S_1(t)/S_2(t)) + \sigma^2(\tau - t)/2}{\sqrt{\sigma^2(\tau - t)}}, \quad d_2 = d_1 - \sqrt{\sigma^2(\tau - t)} \\
\text{and} \quad \sigma &= \sqrt{\sigma_1^2 - 2\rho\sigma_1\sigma_2 + \sigma_2^2}
\end{aligned}
$$

where ρ is the correlation between the two underlyings. For $K \neq 0$ no easy analytic formula is available.

Spread Option Value and Correlation

The value of a spread option depends strongly on the correlation between the two underlyings.

$S_1 = S_2 = 100, \tau = 3, r = 0.02, \sigma_1 = 0.6, \sigma_2 = 0.4.$



- The higher the correlation between the two underlyings the lower is the volatility of the spread and hence the value of the spread option.

Approximative Spread Option Valuation

- A very good reference is Carmona, Durrleman (2003), Siam Review 45 (4), 627-685.
- There is also a survey by Krekel, de Kok, Korn, Man in Wilmott Magazine (2004) available.

Clean Spread Option Valuation

- R.Carmona, M. Coulon, D. Schwarz (2012) present a valuation approach using a full structural model
  - the difference between reduced form models (which we use) and the structural model is relatively small for high-efficiency gas plants, but reduced-form overprices for low-efficiency plants
  - we also define the power price exogeneously
- An accurate approximation formula for the three asset case is also given in E.Alos, A.Eydeland and P.Laurence, Energy Risk, (2011).

Parameter Uncertainty

To use models we need to specify the parameters

- estimation
  - some estimator $\hat{\vartheta}$ is used instead the true parameter ϑ
  - bias and volatility of the estimator have to be considered
- calibration
  - search for parameter that minimizes some pricing error condition, e.g.

$$\vartheta_c = \operatorname*{argmin}_{\vartheta} \left| \sum_{\text{set of derivatives}} \text{model price}(\vartheta) - \text{market price} \right|$$

  - parameters may not be uniquely identified
- Both approaches
  - produce parameter uncertainty,
  - may disregard information.

Parameter uncertainty set-up

- $(\Omega, \mathcal{F}, \mathbb{F})$ filtered measurable space
- $S = (S_t)$ basic instruments, contingent claim $X = F(S)$
- parametrized family of (martingale) measures $(\mathbb{Q}_\theta)_{\theta \in \Theta}$ on $(\Omega, \mathcal{F})$.
- parameter $\theta \in \Theta$, (risk neutral) value of contingent claim is

$$\theta \to \mathbb{E}_\theta(X) := \mathbb{E}_{\mathbb{Q}_\theta}(X).$$

Bannör-Scherer Approach

- distribution R for likelihood of parameter on parameter space Θ available
- convex risk measures gauge extent of parameter risk
- this allows to calculate parameter risk-induced spreads
- Advantages
  - parameter's distribution is exploited
  - risk aversion can be incorporated without being maximally conservative
  - Cont's (2006, Math. Finance, 16(3), 519 -547) suggestion is an extreme points

Convex Risk Measures

Let $(\Omega, \mathcal{F})$ be a measurable space and $\mathcal{X} \subset \mathcal{L}^0(\Omega)$ a vector space. $\mathcal{Y} \subset \mathcal{X}$ be a sub-vector space and $\pi \in \mathcal{Y}^*$.

$$\rho : \mathcal{X} \to \mathbb{R} \tag{2}$$

is a convex risk measure with π translation invariance iff

- ρ is monotone:
$$X \geq Y \implies \rho(X) \geq \rho(Y).$$
- ρ is convex:
$$\forall \lambda \in [0, 1] : \rho(\lambda X + (1 - \lambda) Y) \leq \lambda \rho(X) + (1 - \lambda) \rho(Y).$$
- ρ is π-translation invariant:
$$\forall Y \in \mathcal{Y} : \rho(X + Y) = \rho(X) + \pi(Y).$$

Convex Risk Measures – Properties

- ρ is coherent $\Leftrightarrow$ $\rho(cX) = c\rho(X), \ \forall c > 0$.
- ρ is normalized $\Leftrightarrow$ $\rho(0) = 0$.
- Let $\mathbb{P}$ be a probability measure on $(\Omega, \mathcal{F})$.
  ρ is $\mathbb{P}$-law invariant $\Leftrightarrow$ $\mathbb{P}^X = \mathbb{P}^Y$ implies $\rho(X) = \rho(Y)$.

Risk Capturing Functionals

We denote the space of all derivatives by

$$\mathcal{D} := \bigcap_{\theta \in \Theta} L^1(\mathbb{Q}_\theta) \tag{3}$$

We call

$$\Gamma : \mathcal{D} \to \mathbb{R}$$

a risk-capturing functional with properties

- order preservation $X \geq Y \;\Rightarrow\; \Gamma(X) \geq \Gamma(Y)$
- diversification
  $\forall\, \lambda \in [0,1] :\; \Gamma(\lambda X + (1-\lambda)Y) \leq \lambda \Gamma(X) + (1-\lambda)\Gamma(Y).$
- parameter independence consistency

$$\theta \to \mathbb{E}_\theta(X) \equiv \text{constant} \;\Rightarrow\; \Gamma(X) = \mathbb{E}_\theta(X).$$

Model Risk – Cont's Suggestion

- For X a derivative we associate with $\Gamma(X)$ the ask price and with $-\Gamma(-X)$ its bid price.
- Cont's suggestion

$$\Gamma^u(X) = \sup_{\mathbb{Q}\in\mathcal{Q}} \mathbb{E}_{\mathbb{Q}} \text{ and } \Gamma^l(X) = -\Gamma^u(-X) = \inf_{\mathbb{Q}\in\mathcal{Q}} \mathbb{E}_{\mathbb{Q}}.$$

This approach produces typically a wide bid-ask spread.

Construction of Risk Capturing Functionals

- R a probability measure on Θ
- Let $\mathcal{A} \subset L^0(R)$ be a vector space of measurable functions containing the constants

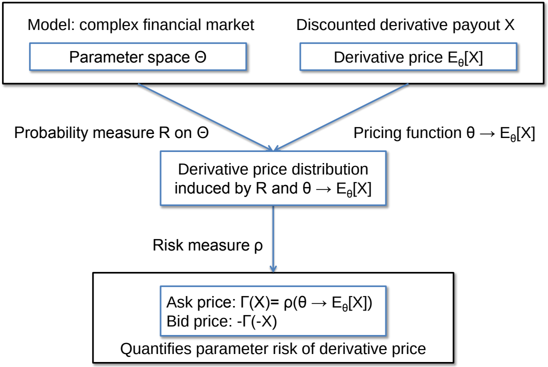
$$\mathcal{D}^{\mathcal{A}} := \left\{ X \in \bigcap_{\theta \in \Theta} L^1(\mathbb{Q}_\theta) : \theta \to \mathbb{E}_\theta(X) \in \mathcal{A} \right\} \tag{4}$$

- $\rho : \mathcal{A} \to \mathbb{R}$ be convex risk measure (normalized, law-invariant)
- Define the parameter risk capturing function

$$\Gamma : \mathcal{D}^{\mathcal{A}} \to \mathbb{R}, \ \Gamma(X) = \rho\left(\theta \to \mathbb{E}_\theta(X)\right) \tag{5}$$

UNIVERSITÄT DUISBURG ESSEN

Parameter Risk-Capturing Valuation



Definition AVaR

- general probability space $(\Omega, \mathcal{F}, \mathbb{P})$, $\beta \in (0, 1]$, $X \in L^1(\mathbb{P})$, then
$$VaR_\beta(X) = q^{\mathbb{P}}_{-X}(1 - \beta).$$
- the average value at risk at level $\alpha \in (0, 1]$ is
$$AVaR_\alpha(X) = \frac{1}{\alpha} \int_0^\alpha VaR_\beta(X) d\beta.$$
- AVaR_α is a convex risk measure (coherent and law-invariant).

Definition AVaR risk capturing functional

- Assume a parametrized family of (martingale) measures $\mathcal{Q}_\Theta = (\mathbb{Q}_\theta)_{\theta\in\Theta}$.
- Let R be a distribution on Θ.
- Consider the $\mathcal{L}^1(R)$ admissible functionals, so $AVaR_\alpha : \mathcal{L}^1(R) \to \mathbb{R}$.
- Define the AVaR_α risk-capturing functional $R \star AVaR_\alpha : \mathcal{C}^{\mathcal{L}^1(R)} \to \mathbb{R}$ as

$$R \star AVaR_\alpha(X) := AVaR_\alpha\left(\theta \to \mathbb{E}_\theta(X)\right).$$

UNIVERSITÄT DUISBURG ESSEN

Convergence Property of AVaR

- Assume $R_N \to R_0, \ (N \to \infty)$ weakly on $\mathcal{Q}_\Theta$;
- ρ_N a sequence of convex risk measures with ρ_N is R_N invariant;
- A sequence Γ_N with $\Gamma_N = \rho_N \left(\mathcal{Q}_\Theta \to \mathbb{E}_\theta(X) \right)$ has the convergence property (CP) if and only if

$$\lim_{N \to \infty} \Gamma_N(X) = \Gamma_0(X) = \rho_0 \left(\mathcal{Q}_\Theta \to \mathbb{E}_\theta(X) \right) \ \forall X \in C^{\mathcal{A}}.$$

- AVaR -induced risk-capturing functionals fulfill (CP) for Θ compact.

Using asymptotic distributions

- (CP) allows us, if the parameter distribution R is complicated to calculate or even unknown, to use a parameter distribution $\tilde{R}$ which is "close" to the original distribution R (in the sense of weak convergence, like, e.g., some asymptotic distribution) and calculate the risk-captured price with the parameter distribution $\tilde{R}$ instead.
- In particular, if the distribution R is propagated from an estimator $\hat{\theta}_N$ and the asymptotic distribution of the estimator $\hat{\theta}_N$ is known (let us, e.g., denote the asymptotic distribution by R_∞), we can use the distribution R_∞ instead, if the sample size $N \in \mathbb{N}$ is large enough.

UNIVERSITÄT DUISBURG ESSEN

Calculating AVaR

- Assume $(\theta_N)_{N\in\mathbb{N}}$ is an asymptotically normal sequence of estimators for the true parameter $\theta_0 \in \Theta \subset \mathbb{R}_m$ with positive definite covariance matrix Σ, so

$$\sqrt{N}\left(\theta_N - \theta_0\right) \to \mathcal{N}_m\left(0, \Sigma\right).$$

- If $\theta \mapsto \mathbb{E}_\theta(X)$ is continuously differentiable and $\nabla\mathbb{E}_{\theta_0} \neq 0$, then

$$\sqrt{N}\left(\mathbb{E}_{\theta_N}(X) - \mathbb{E}_{\theta_0}(X)\right) \to \mathcal{N}\left(0, \left(\nabla\mathbb{E}_{\theta_0}\right)' \Sigma \nabla\mathbb{E}_{\theta_0}\right)$$

- For $\theta_N \star AVaR_\alpha(X)$ we calculate the AVaR as for a normally distributed variable

$$\theta_N \star AVaR_\alpha(X) \approx \mathbb{E}_{\theta_0}(X) + \frac{\varphi\left(\Phi^{-1}(\alpha)\right)}{\alpha\sqrt{N}}\sqrt{\left(\nabla\mathbb{E}_{\theta_0}\right)' \Sigma \nabla\mathbb{E}_{\theta_0}},$$

Emission Certificates

We model the emission price as a geometric Brownian motion

$$\mathrm{d}E_t = \alpha^E E_t \,\mathrm{d}t + \sigma^E E_t \,\mathrm{d}W_t^E, \tag{6}$$

Gas Price

- We model the gas price as a mean-reverting process

$$
\begin{aligned}
G_t &= e^{g(t)+Z_t}, \\
\mathrm{d}Z_t &= -\alpha^G Z_t \,\mathrm{d}t + \sigma^G \,\mathrm{d}W_t^G,
\end{aligned}
\tag{7}
$$

- α^G is the speed of mean-reversion for gas prices.

Power Price

- We model the power price as a sum of two mean-reverting processes

$$
\begin{aligned}
P_t &= e^{f(t)+X_t+Y_t}, \\
\mathrm{d}X_t &= -\alpha^P X_t \,\mathrm{d}t + \sigma^P \,\mathrm{d}W_t^P, \\
\mathrm{d}Y_t &= -\beta \, Y_t \,\mathrm{d}t + J_t \,\mathrm{d}N_t,
\end{aligned} \tag{8}
$$

- α^P and β are speeds of mean-reversion for the smooth and the jump component of power prices.
- N is a Poisson process with intensity λ.
- J_t are independent identically distributed (i.i.d) random variables representing the jump size.

Seasonal components

$g(t)$ and $f(t)$ are seasonal trend components for gas and power, respectively, defined as

$$\begin{aligned} f(t) &= a_1 + a_2\, t + a_3 \cos(a_5 + 2\pi t) + a_4 \cos(a_6 + 4\pi t), \\ g(t) &= b_1 + b_2\, t + b_3 \cos(b_5 + 2\pi t) + b_4 \cos(b_6 + 4\pi t), \end{aligned} \tag{9}$$

where a_1 and b_1 may be viewed as production expenses, a_2 and b_2 are the slopes of increase in these costs. The rest of the parameters are responsible for two seasonal changes in summer and winter respectively.

Dependence Structure

In the current setting we also assume that W^E, W^G and N are mutually independent processes, but there is some correlation between W^P and W^G

$$\mathrm{d}W_t^P \,\mathrm{d}W_t^G = \rho \,\mathrm{d}t. \tag{10}$$

Parameter Uncertainty

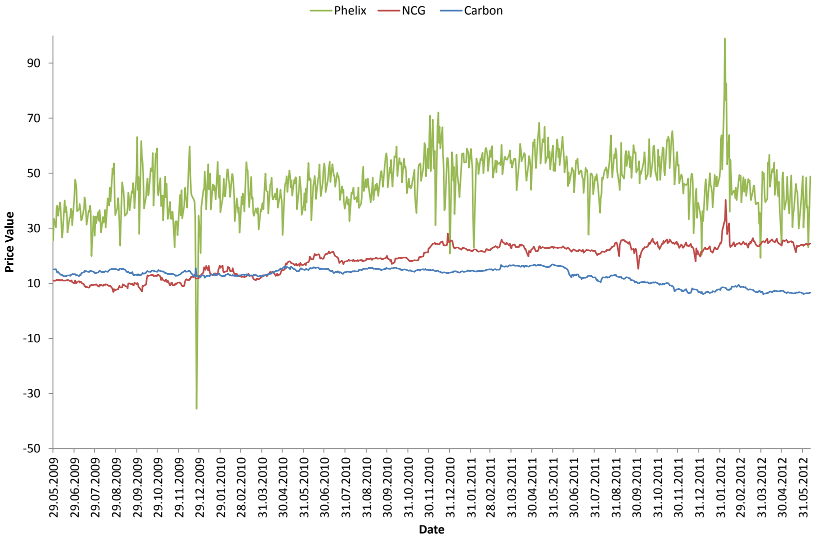
- The total set of parameters includes $\{\alpha^E, \sigma^E, g(t), \alpha^G, \sigma^G, f(t), \alpha^P, \beta, \sigma^P, \lambda, \mathbb{E}[J], \mathbb{E}[J^2], \rho\}$.
- Hence, the hybrid model we have chosen for modelling the clean spark spread is not parsimonious and allows for several degrees of freedom.
- Consequently, the risk of determining parameters in a wrong way is considerable.

Data sources

- Phelix Day Base: It is the average price of the hours 1 to 24 for electricity traded on the spot market. It is calculated for all calendar days of the year as the simple average of the auction prices for the hours 1 to 24 in the market area Germany/Austria. (EUR/MWh),
- NCG: Delivery is possible at the virtual trading hub in the market areas of NetConnect Germany GmbH & Co KG. daily price (EUR/MWh),
- Emission certificate daily price: One EU emission allowance confers the right to emit one tonne of carbon dioxide or one tonne of carbon dioxide equivalent. (EUR/EUA).
- We cover the last three years: 25.09.2009 - 08.06.2012.

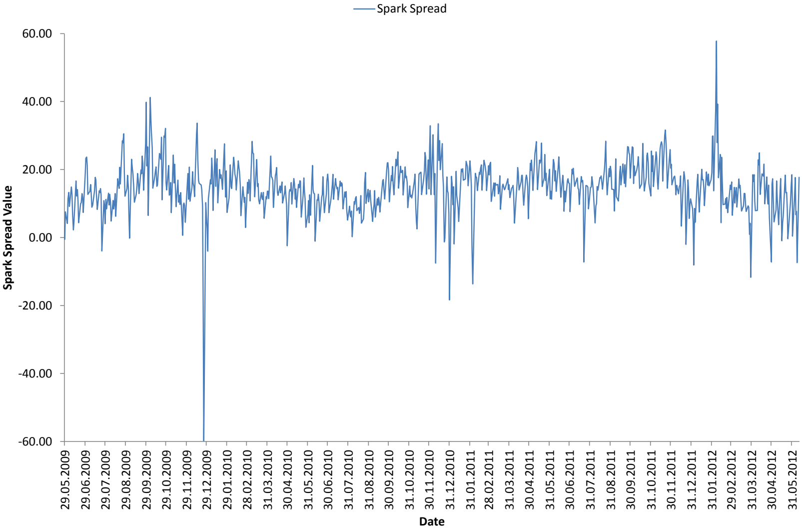
UNIVERSITÄT DUISBURG ESSEN

Price Paths, 25.09.2009 - 08.06.2012.



UNIVERSITÄT DUISBURG ESSEN

Clean Spark Spread, 25.09.2009 - 08.06.2012.



Emissions and Gas

- Apply a standard procedure to de-seasonalize gas (don't change notation).
- $\log E_t$ and $\log G_t$ are normally distributed.
- Thus, we can use standard Maximum Likelihood Methods.

Power I

The estimation procedure for the power price includes several steps:

- Estimation of the seasonal trend and deseasonalisation.
- With an iterative procedure we filter out returns with absolute values greater than three times the standard deviation of the returns of the series at the current iteration. The process is repeated until no further outliers can be found.
- As a result we obtain a standard deviation of the jumps, σ_j, and a cumulative frequency of jumps, l. The latter is defined as the total number of filtered jumps divided by the annualised number of observations.

Power II

- Once we have filtered the X_t process, we can identify it as a first order autoregressive model in continuous time, i.e. so-called AR(1) process. Discretizing the process and estimating it by maximum likelihood method (MLE) yields the estimates.

UNIVERSITÄT DUISBURG ESSEN

Estimation Results

Estimation Step	Product	Estimates	Method
GBM	Emissions	$\alpha^E = -0.2843$, $\sigma^E = 0.4079$	MLE
Seasonal trend	Power	$a_1 = 3.6716$, $a_2 = 0.0980$, $a_3 = -0.0274$ $a_4 = 0.0368$, $a_5 = 0.6524$, $a_6 = 0.9530$	OLS
Seasonal trend	Gas	$b_1 = 2.3420$, $b_2 = 0.3503$, $b_3 = 0.0218$ $b_4 = -0.0445$, $b_5 = 0.7829$, $b_6 = 1.6126$	OLS
Filtering	Power		$3\times$Std.Dev rule
Base process	Gas	$\alpha^G = 13.5827$, $\sigma^G = 0.7768$	Multivariate
Base process	Power	$\alpha^P = 121.8684$, $\sigma^P = 2.5943$, $\rho = 0.1247$	normal regression
Spike mean-reversion	Power	$\beta = 243.7240$	
Spike intensity	Power	$\lambda = 13.4936$	Annual frequency
Spike size (Laplace)	Power	$\mu_s(median) = 0.3975$, $\sigma_s(scale) = 0.6175$	MLE
Spike size (normal)	Power	$\mu_s(mean) = 0.0863$, $\sigma_s(variance) = 0.5857$	MLE
Heat rate	Gas	$h = 2.5$	
Interest rate		$r = 3\%$	

UNIVERSITÄT DUISBURG ESSEN

We will be capturing model risk in

- Jump size distribution;
- Correlation;
- Gas alone;
- Gas and power base signal;
- Gas, power and emissions (all the parameters, except of jump size).

General Procedure

- We reduce the problem here by considering the distributions of the single parameters separately (e.g. the correlation coefficient, the jump size distribution parameters). Hence, we do some kind of "sensitivity analysis" w.r.t. different parameters, disregarding the remaining parameter risk.
- Each parameter θ_j is to be estimated by an estimator $\hat{\theta}_j(X_1, \ldots, X_N)$ under the real-world measure and we assume the other parameters $\theta_1, \ldots, \theta_{j-1}, \theta_{j+1}, \theta_N$ to be known. We use plug-in estimators as the true values and figure out the asymptotic distribution of the estimators.
- We calculate the parameter risk-captured prices which are generated by the Average-Value-at-Risk (AVaR) w.r.t. different significance levels $\alpha \in (0, 1]$.

Spark Spread Analysis I

In our investigation we will focus on the clean spark spread to model the value of virtual gas power plant. We will use spot price processes in order to assess the day-by-day risk position of such a plant. Thus, we will model the daily profit (or loss) of a power plant as

$$V_t = \max\{P_t - h\,G_t - c_E\,E_t, 0\}, \tag{11}$$

where P_t is the power price, G_t is the gas price, E_t is the carbon certificate price, h is the heat rate, c_E emission conversion rate.

Spark Spread Analysis II

- We compute the spark spread value V_t given in (11) for every day t for a time period of three years.
- Then, by fixing all the parameters except of one (e.g. correlation) and setting the shift value (e.g. 1%), we compute shifted up and down spark spread values, i.e. V_t^{up} and V_t^{down}.

UNIVERSITÄT DUISBURG ESSEN

Power Plant Analysis I

We compute the value of the power plant (VPP) by means of Monte Carlo simulations. For a fixed large number N and a fixed period $T = 3$ years we have

$$VPP(t,T) = \frac{1}{N}\sum_{i=1}^{N} VPP_i(t,T),$$

where

$$VPP_i(t,T) = \sum_{s=t}^{T} e^{-r(T-s)}\, V_i(s).$$

Power Plant Analysis II

- We also compute shifted both up and down power plant values, i.e. $VPP^{up}(t,T)$ and $VPP^{down}(t,T)$ (i.e. w.r.t. shifted spark spread values) and calculate the sensitivity

$$sVPP(\theta_0) = \frac{VPP^{up}(t,T) - VPP^{down}(t,T)}{2 \cdot shift}.$$

- Finally, we compute the bid and ask prices, i.e. we use the closed formula for AVaR to get the risk-captured prices by subtracting and adding risk-adjustment value to $VPP(t,T)$ respectively.
- For a specified significance level $\alpha \in (0,1)$ this risk-adjustment value is computed as

$$\frac{\varphi(\Phi^{-1}(\alpha))}{\alpha}\sqrt{\frac{sVPP(\theta_0)' \cdot \Sigma \cdot sVPP(\theta_0)}{N}}.$$

Correlation: the Estimator and its Distribution

- We have correlation between the base signal X_t of power price and the log gas price $logG_t$ implied by the driving Brownian motions
- Let x_i and y_i, $1 = 1, \dots n$ the corresponding discrete observations, then we use Pearson's sample coefficient

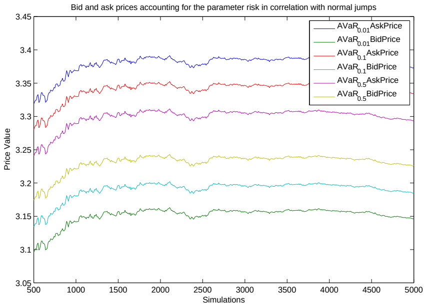
$$\rho^{(n)} = \frac{n \sum_{i=1}^{n} x_i y_i - \left(\sum_{i=1}^{n} x_i\right)\left(\sum_{i=1}^{n} y_i\right)}{\sqrt{\sum_{i=1}^{n} x_i^2 - \left(\sum_{i=1}^{n} x_i\right)^2}\sqrt{\sum_{i=1}^{n} y_i^2 - \left(\sum_{i=1}^{n} y_i\right)^2}}.$$

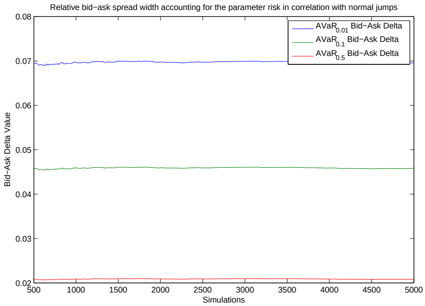
- In our bivariate normal setting we can apply Fisher's transformation and have

$$artanh\left(\rho^{(n)}\right) \sim \mathcal{N}\left(artanh(\rho_0), \frac{1}{n-3}\right)$$

UNIVERSITÄT DUISBURG ESSEN

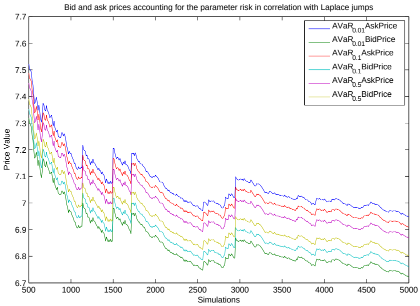
Parameter-risk implied bid-ask spread w.r.t. correlation parameter, Gaussian jumps.

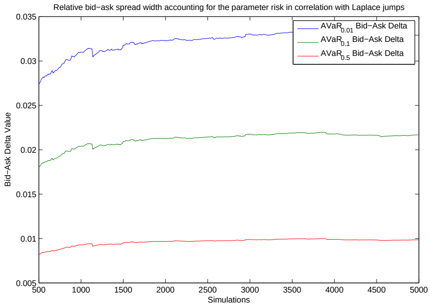




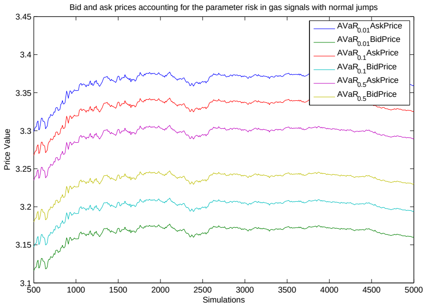
UNIVERSITÄT DUISBURG ESSEN

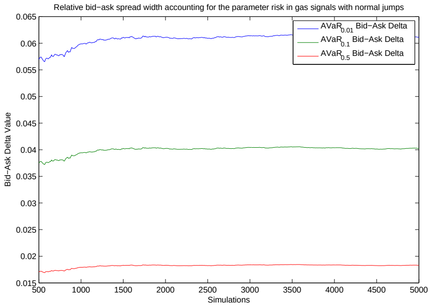
Parameter-risk implied bid-ask spread w.r.t. correlation parameter, Laplace jumps.



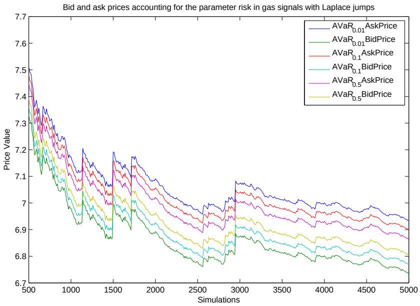


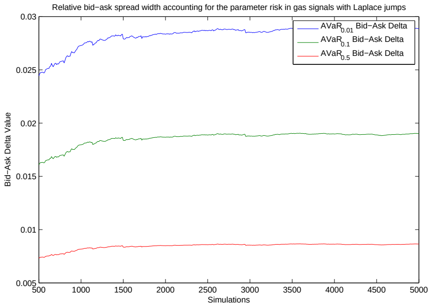
Parameter-risk implied bid-ask spread w.r.t. the gas price process, Gaussian jumps.





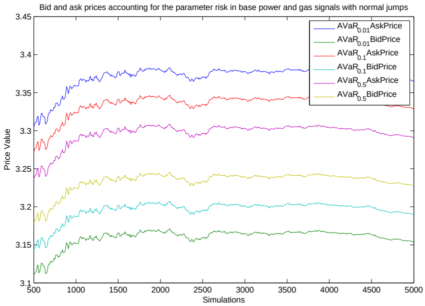
Parameter-risk implied bid-ask spread w.r.t. the gas price process, Laplace jumps.

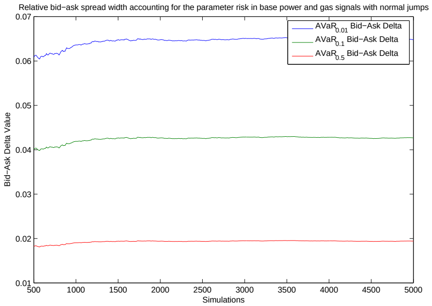




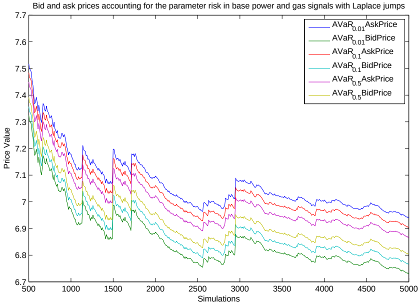
UNIVERSITÄT DUISBURG ESSEN

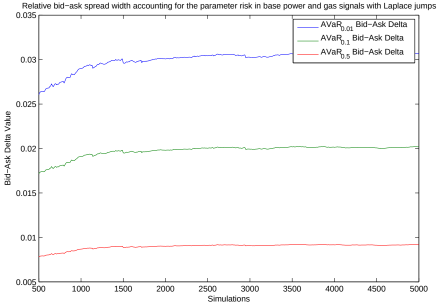
Parameter-risk implied bid-ask spread w.r.t. the gas and power base processes, Gaussian jumps.



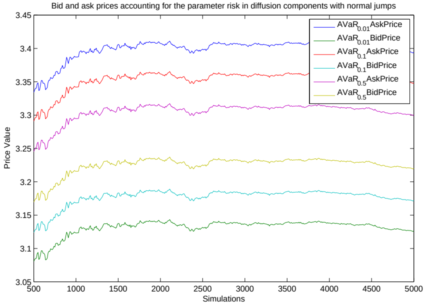


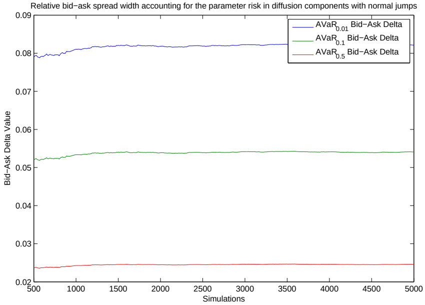
Parameter-risk implied bid-ask spread w.r.t. the gas and power base processes, Laplace jumps.





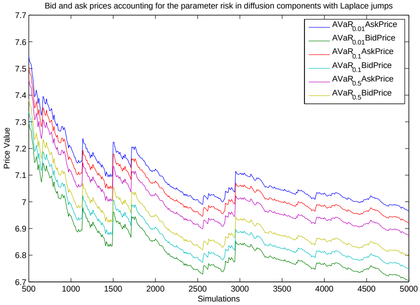
Parameter-risk implied bid-ask spread w.r.t. all the parameters, except of the Gaussian jump size.

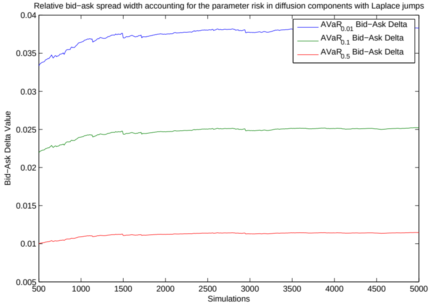




UNIVERSITÄT DUISBURG ESSEN

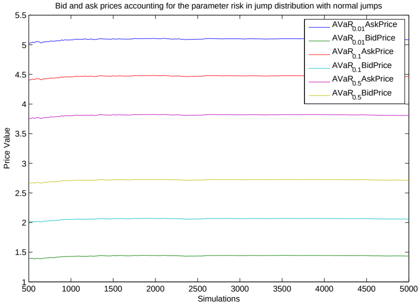
Parameter-risk implied bid-ask spread w.r.t. all the parameters, except of the Laplace jump size.

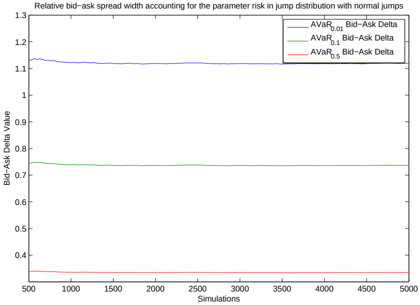




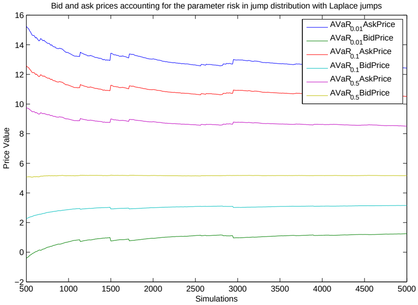
UNIVERSITÄT DUISBURG ESSEN

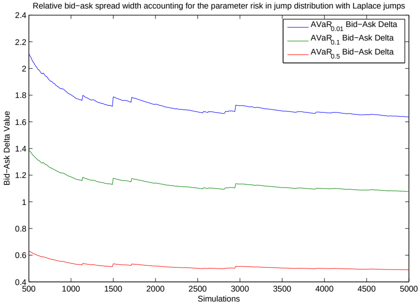
Parameter-risk implied bid-ask spread w.r.t. jump size distribution: Gaussian.





Parameter-risk implied bid-ask spread w.r.t. jump size distribution: Laplace.



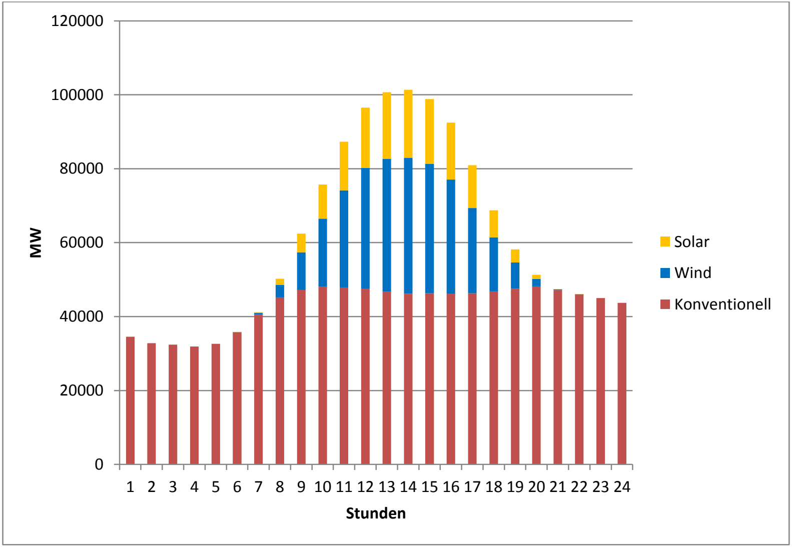


Resulting values for the relative width of the bid-ask spread for various model risk sources. $\alpha_1 = 0.01$, $\alpha_2 = 0.1$, $\alpha_3 = 0.5$.

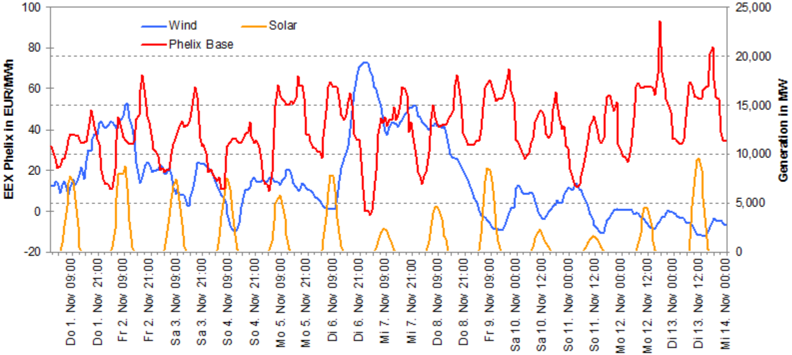
		Jumps size distribution					
		Gaussian			Laplace		
		α_1	α_2	α_3	α_1	α_2	α_3
Model Risk	Jumps	111.9%	73.71%	33.51%	163.5%	107.7%	48.96%
	Correlation	6.95%	4.58%	2.08%	3.29%	2.17%	0.99%
	Gas and power base	6.48%	4.27%	1.94%	3.07%	2.02%	0.92%
	Gas	6.11%	4.03%	1.83%	2.89%	1.91%	0.87%
	Gas, power and carbon	8.21%	5.41%	2.46%	3.83%	2.52%	1.15%

Gas Power Plant

A day in august



Wind, sun and electricity



UNIVERSITÄT DUISBURG ESSEN

RWE Response 14.August 2013

Decision on capacity measures

Measure	Plant	MW[1]	Fuel	Location	Date
Decom-missioning	Amer 8	610	Hard coal	NL	Q1-2016[2]
Long-term mothballing	Moerdijk 2	430	Gas	NL	Q4-2013
	Gersteinwerk F	355	Gas – steam turbine	DE	Q3-2013
	Gersteinwerk G	355	Gas – steam turbine	DE	Q2-2014
	Weisweiler H	270	Topping gas turbine[3]	DE	Q3-2013
	Weisweiler G	270	Topping gas turbine[3]	DE	Q3-2013
	2 mid-size units	85	Gas	NL	Q1-2013
Summer mothballing	Emsland B	360	Gas – steam turbine	DE	Q2-2014
	Emsland C	360	Gas – steam turbine	DE	Q2-2014
Termination of 3 contracts	Confidential	1,170	Hard coal	DE	Q4-2013 – Q4-2014
Total		**4,265 MW**			

[1] Net nominal capacity | [2] Depending on the final decision on the Dutch "Energieakkoord", with a decision expected by the end of August 2013 | [3] At a lignite plant

RWE The energy to lead

RWE AG | H1 2013 Conference Call | 14 August 2013 5

Conclusions

- What we did
  - We suggested a methodology to quantify model risk in power plant valuation approaches (spread options)
  - We studied correlation and spike risk
- What we still need/want to do
  - Perform more and better model analysis: estimation methods, approximation of quantities
  - Improve simulation method: use analytic approaches as benchmarks
  - Discuss multi-variate parameter model risk
  - Study more realistic examples of power plants and valuation methodology
  - Consider other energy derivatives

UNIVERSITÄT DUISBURG ESSEN

Energy & Finance Essen

Energy & Finance Conference in Essen, October 9-11, 2013

UNIVERSITÄT DUISBURG ESSEN

Contact

- Chair for Energy Trading and Finance
  University Duisburg-Essen
  Universitätsstrße 12
  45141 Essen, Germany

  phone +49 (0)201 183-4973
  fax +49 (0)201 183-4974
- web: www.lef.wiwi.uni-due.de

- Thank you for your attention...