



Institute for Operations Research  
and Computational Finance

University of St.Gallen

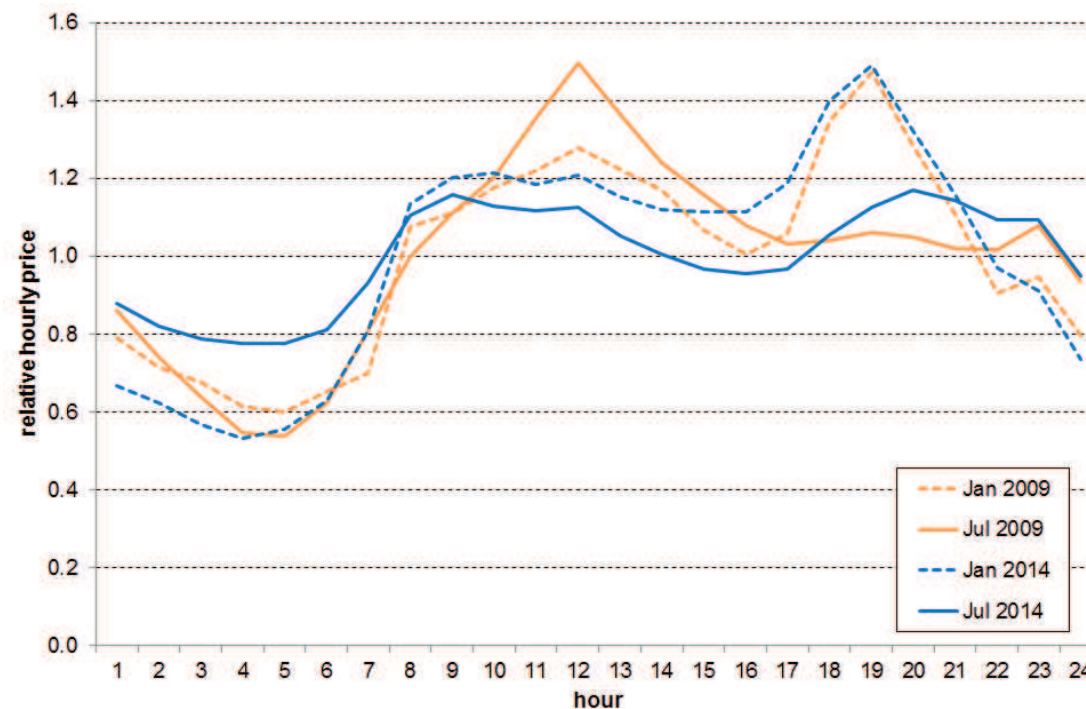
## *A structural model for electricity forward prices*

**Florentina Paraschiv, University of St. Gallen, ior/cf**  
**with Fred Espen Benth, University of Oslo**

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# Outlook

- Structural models for forward electricity prices are highly relevant: major structural changes in the market due to the infeed from renewable energy
- Renewable energies impact the market price expectation – **impact on futures (forward) prices?**
- We will refer to a panel of daily price forward curves derived over time: cross-section analysis with respect to the *time dimension* and the *maturity space*
- Examine and model the dynamics of *risk premia*, the *volatility term structure*, *spatial correlations*



## Literature review

- Models for forward prices in commodity/energy:
  - Specify one model for the spot price and from this derive for forwards: *Lucia and Schwartz (2002)*; *Cartea and Figueroa (2005)*; *Benth, Kallsen, and Mayer-Brandis (2007)*;
  - Heath-Jarrow-Morton approach – price forward prices directly, by multifactor models: *Roncoroni, Guiotto (2000)*; *Benth and Koekebakker (2008)*; *Kiesel, Schindlmayr, and Boerger (2009)*;
- Critical view of *Koekebakker and Ollmar (2005)*, *Frestad (2008)*
  - Few common factors cannot explain the substantial amount of variation in forward prices
  - Non-Gaussian noise
- Random-field models for forward prices:
  - *Roncoroni, Guiotto (2000)*;
  - *Andresen, Koekebakker, and Westgaard (2010)*;
- Derivation of seasonality shapes and price forward curves for electricity:
  - *Fleten and Lemming (2003)*;
  - *Bloechlinger (2008)*.

## Problem statement

- Previous models model forward prices evolving over time (time-series) along the **time at maturity  $T$** : *Andresen, Koekebakker, and Westgaard (2010)*
- Let  $F_t(T)$  denote the forward price at time  $t \geq 0$  for delivery of a commodity at time  $T \geq t$

- Random field in  $t$ :

$$t \mapsto F_t(T), \quad t \geq 0 \quad (1)$$

- Random field in both  $t$  and  $T$ :

$$(t, T) \mapsto F_t(T), \quad t \geq 0, \quad t \leq T \quad (2)$$

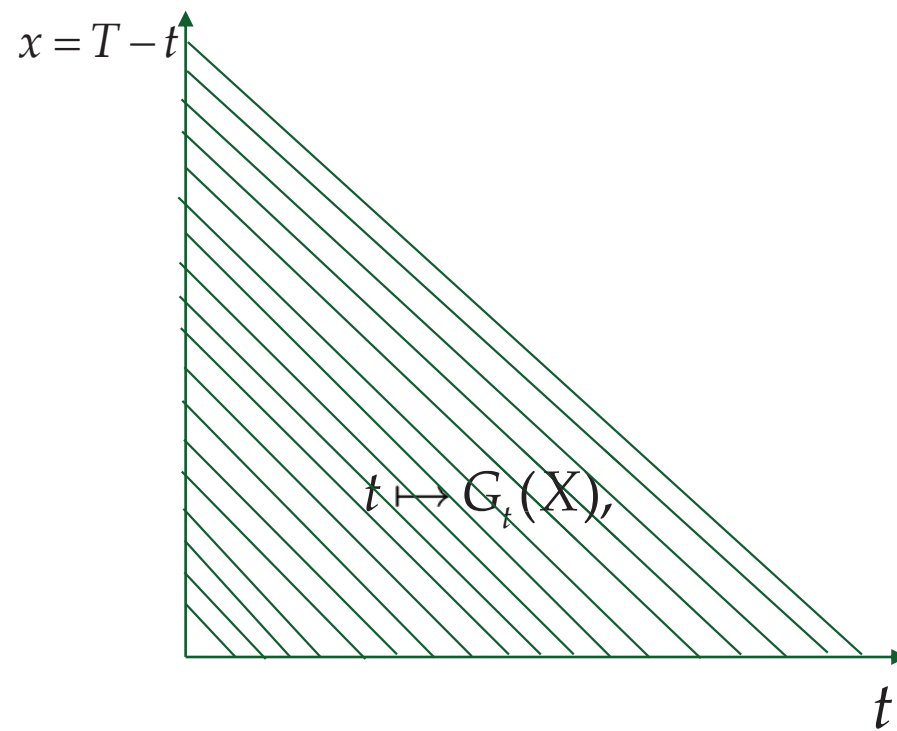
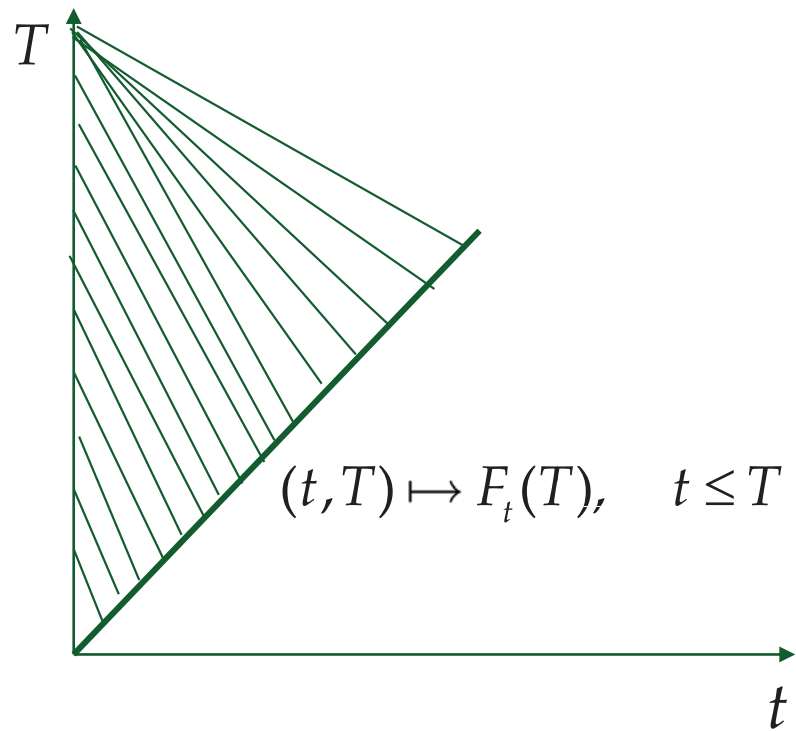
- Get rid of the second condition: **Musiela parametrization**  $x = T - t$ ,  $x \geq 0$ .

$$F_t(t + x) = F_t(T), \quad t \geq 0 \quad (3)$$

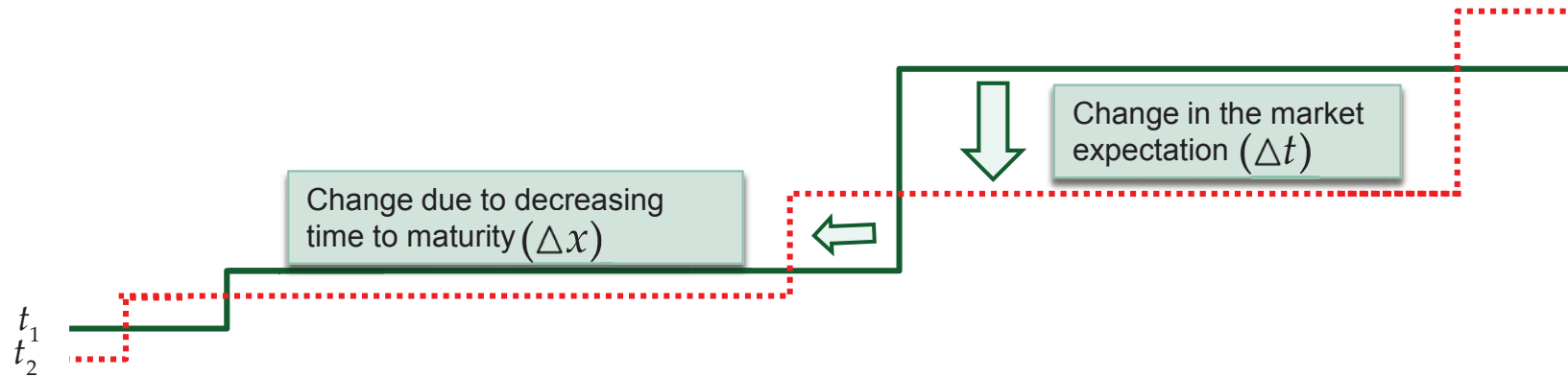
- Let  $G_t(x)$  be the forward price for a contract with time to maturity  $x \geq 0$ . Note that:

$$G_t(x) = F_t(t + x) \quad (4)$$

## Graphical interpretation



## Influence of the “time to maturity”



## Model formulation: Heath-Jarrow-Morton (HJM)

- The stochastic process  $t \mapsto G_t(x)$ ,  $t \geq 0$  is the solution to:

$$dG_t(x) = (\partial_x G_t(x) + \beta(t, x)) dt + dW_t(x) \quad (5)$$

- Space of curves are endowed with a Hilbert space structure  $\mathcal{H}$
- $\partial_x$  differential operator with respect to time to maturity
- $\beta$  spatio-temporal random field describing the market price of risk
- $W$  Spatio-temporal random field describing the randomly evolving residuals
- Discrete structure:

$$G_t(x) = f_t(x) + s_t(x), \quad (6)$$

- $s_t(x)$  deterministic seasonality function  $\mathbb{R}_+^2 \ni (t, x) \mapsto s_t(x) \in \mathbb{R}$

## Model formulation (cont)

We furthermore assume that the deasonalized forward price curve, denoted by  $f_t(x)$ , has the dynamics:

$$df_t(x) = (\partial_x f_t(x) + \theta(x)f_t(x)) dt + dW_t(x), \quad (7)$$

with  $\theta \in \mathbb{R}$  being a constant. With this definition, we note that

$$\begin{aligned} dF_t(x) &= df_t(x) + ds_t(x) \\ &= (\partial_x f_t(x) + \theta(x)f_t(x)) dt + \partial_t s_t(x) dt + dW_t(x) \\ &= (\partial_x F_t(x) + (\partial_t s_t(x) - \partial_x s_t(x)) + \theta(x)(F_t(x) - s_t(x))) dt + dW_t(x). \end{aligned}$$

In the natural case,  $\partial_t s_t(x) = \partial_x s_t(x)$ , and therefore we see that  $F_t(x)$  satisfy (5) with  $\beta(t, x) := \theta(x)f_t(x)$ .

The market price of risk is proportional to the deseasonalized forward prices.



## Model formulation (cont)

We discretize the dynamics in Eq. (7) by an Euler discretization

$$df_t(x) = (\partial_x f_t(x) + \theta(x)f_t(x)) dt + dW_t(x)$$

$$\partial_x f_t(x) \approx \frac{f_t(x + \Delta x) - f_t(x)}{\Delta x}$$

$$f_{t+\Delta t}(x) = (f_t(x) + \frac{\Delta t}{\Delta x}(f_t(x + \Delta x) - f_t(x)) + \theta(x)f_t(x)\Delta t + \epsilon_t(x) \quad (8)$$

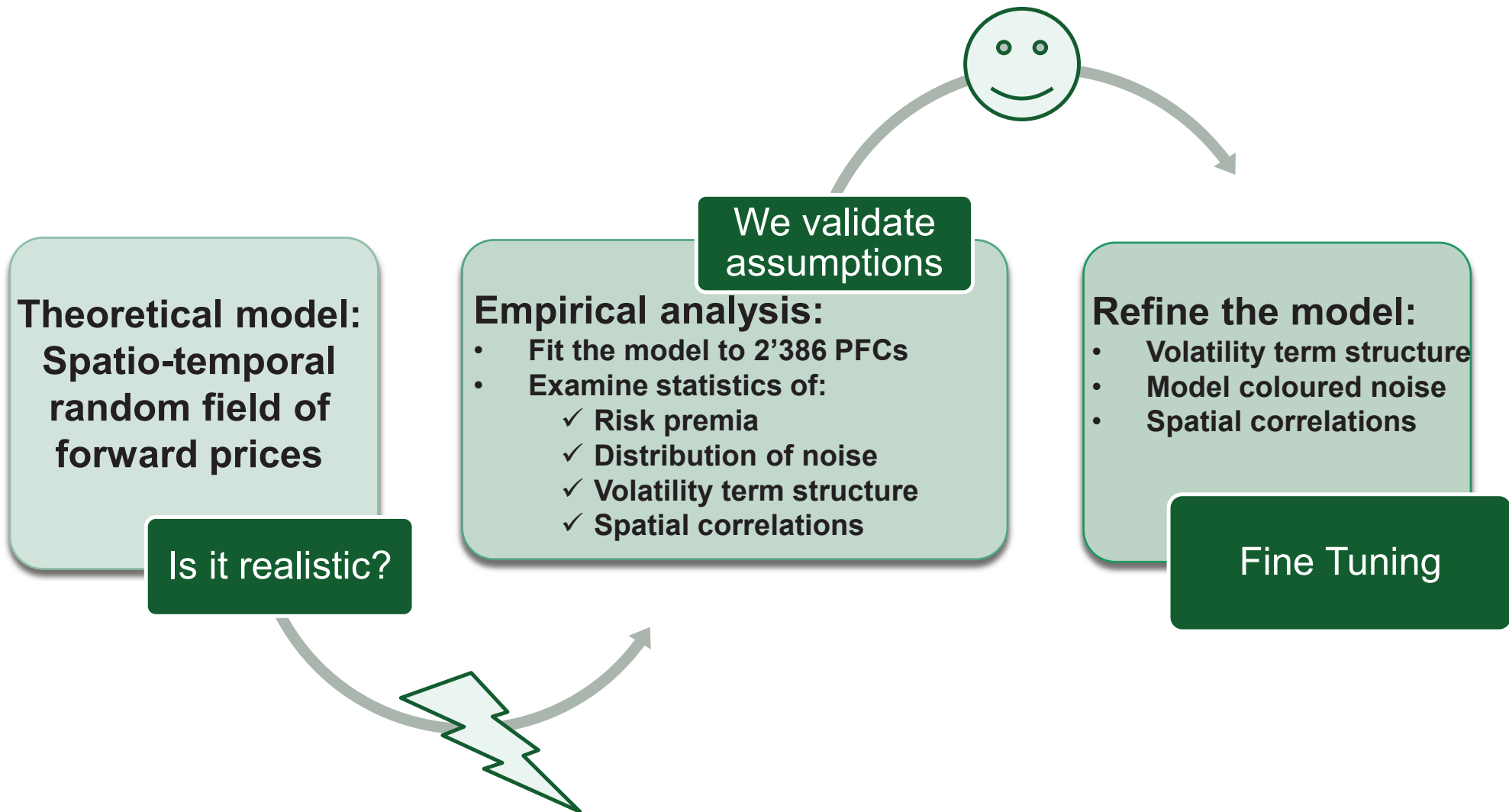
with  $x \in \{x_1, \dots, x_N\}$  and  $t = \Delta t, \dots, (M-1)\Delta t$ , where  $\epsilon_t(x) := W_{t+\Delta t}(x) - W_t(x)$ .

$$Z_t(x) := f_{t+\Delta t}(x) - f_t(x) - \frac{\Delta t}{\Delta x}(f_t(x + \Delta x) - f_t(x)) \quad (9)$$

which implies

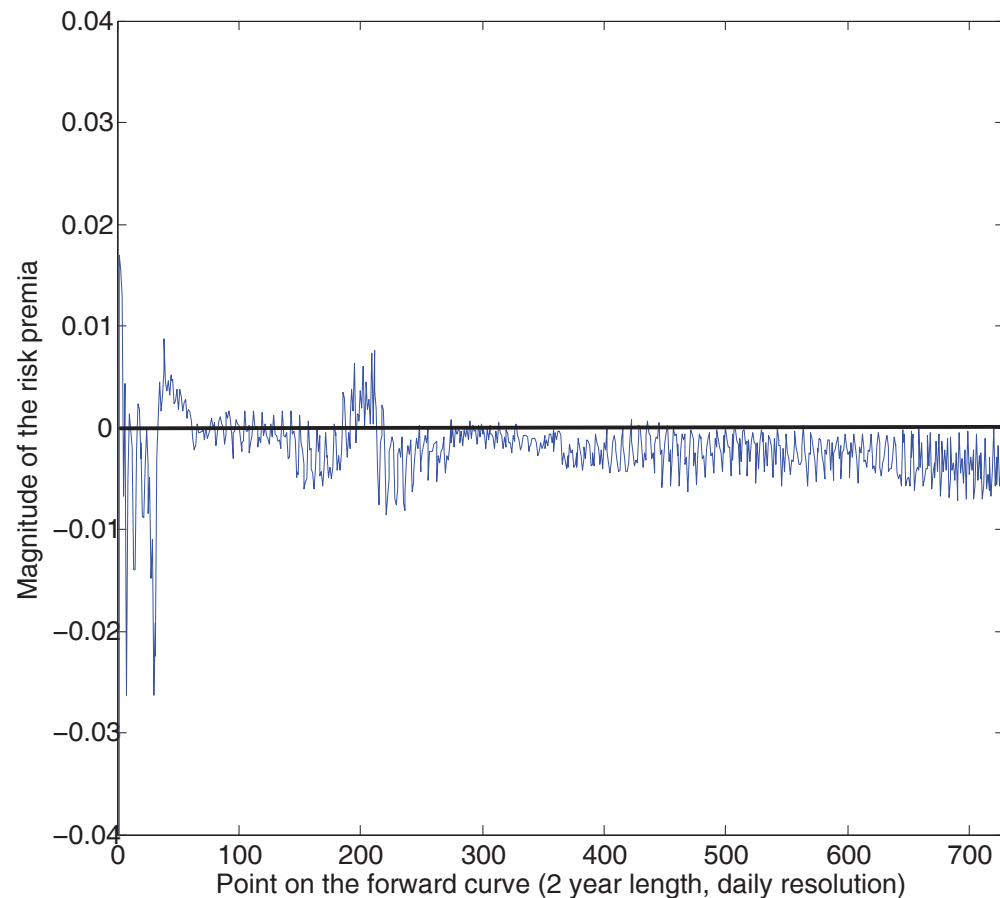
$$Z_t(x) = \theta(x)f_t(x)\Delta t + \epsilon_t(x), \quad (10)$$

$$\epsilon_t(x) = \sigma(x)\tilde{\epsilon}_t(x) \quad (11)$$



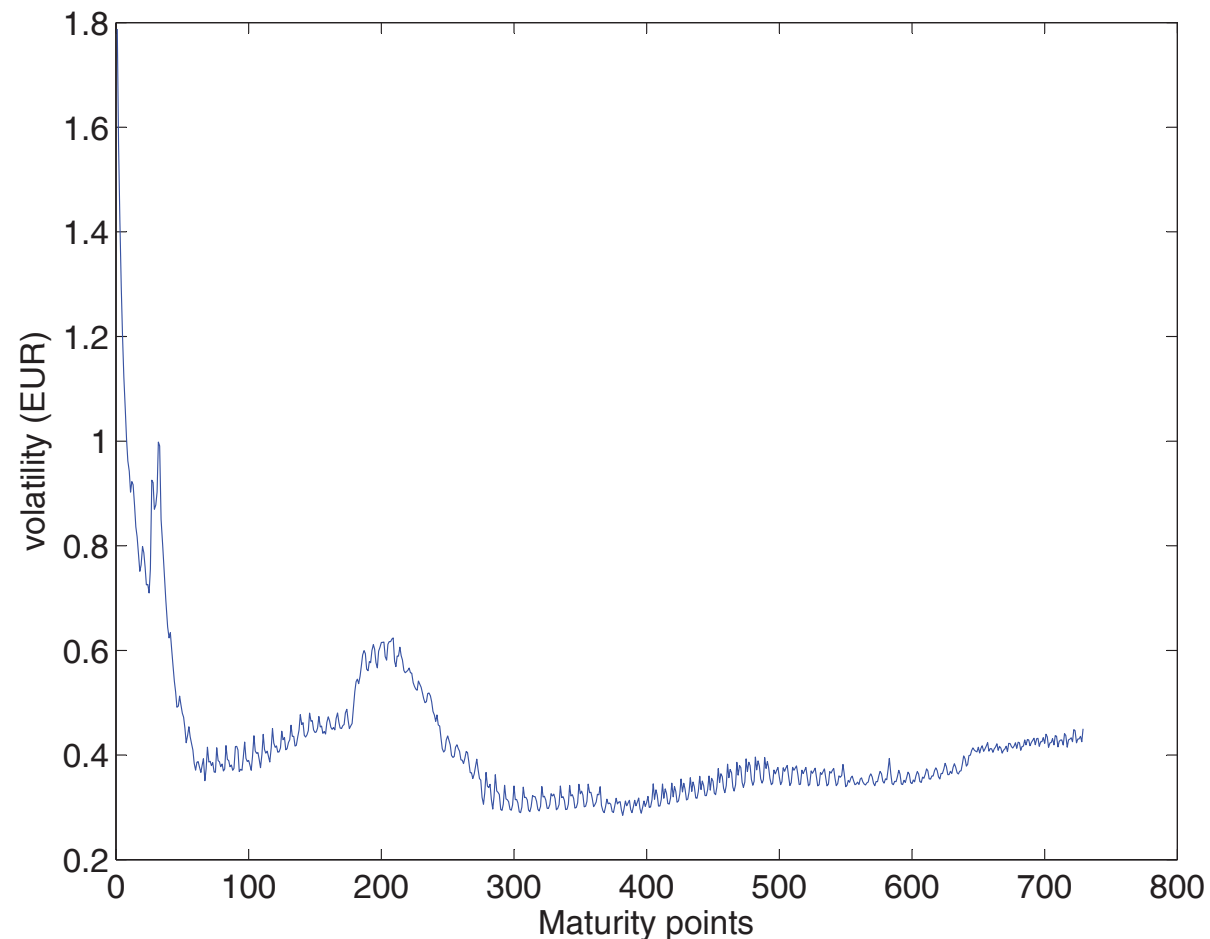
## Risk premia

- Short-term: it oscillates around zero and has higher volatility (similar in *Pietz (2009)*, *Paraschiv et al. (2015)*)
- Long-term: it becomes negative and has more constant volatility (*Burger et al. (2007)*): In the long-run power generators accept lower futures prices, as they need to make sure that their investment costs are covered.



## Term structure volatility

- We observe Samuelson effect: overall higher volatility for shorter time to maturity
- Volatility bumps (front month; second/third quarters) explained by increased volume of trades
- Jigsaw pattern: weekend effect; volatility smaller in the weekend versus working days



## Explaining volatility bumps

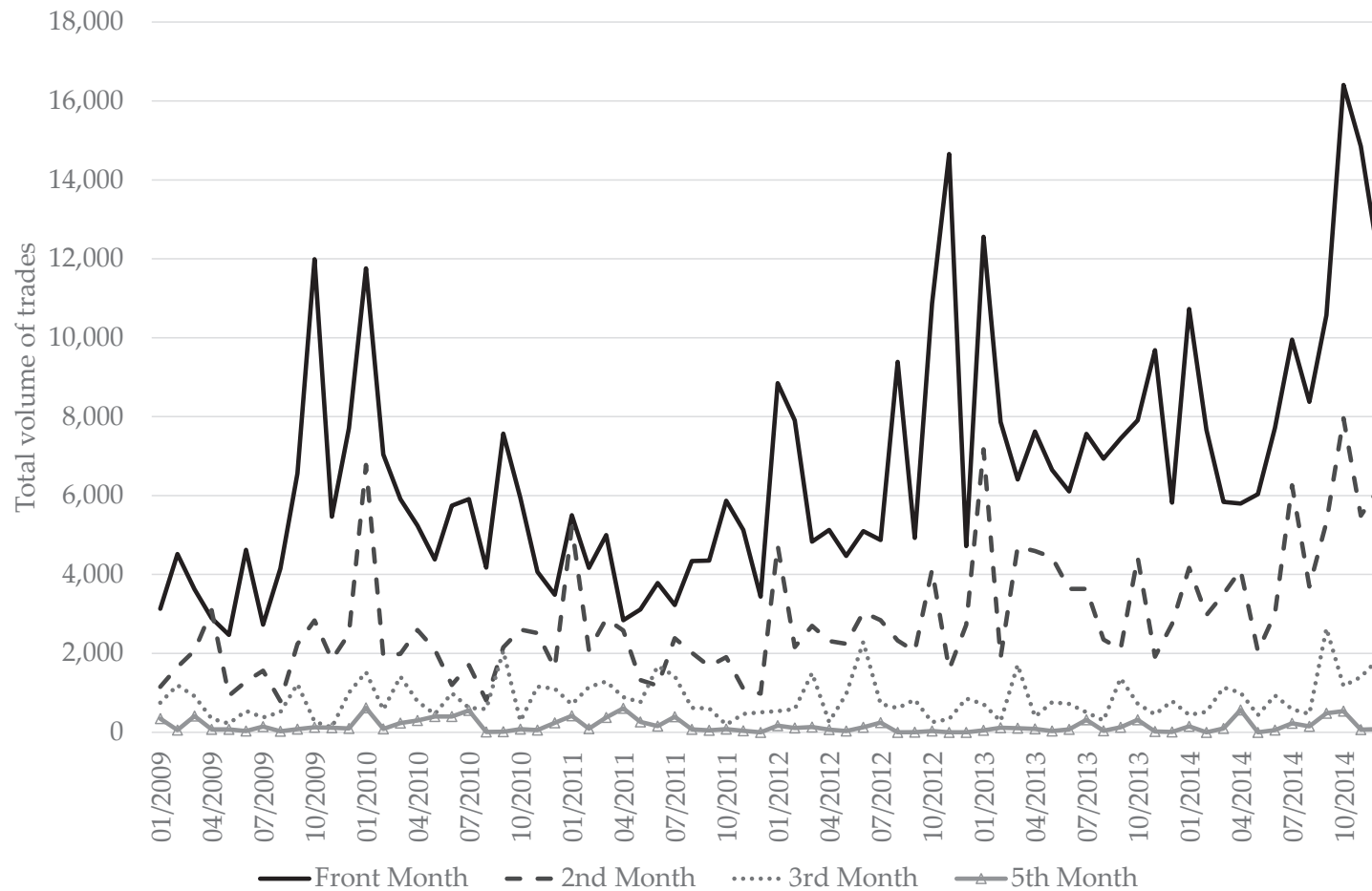


Figure 2: The sum of traded contracts for the monthly futures, evidence from EPEX, own calculations (source of data [ems.eex.com](http://ems.eex.com)).

## Explaining volatility bumps

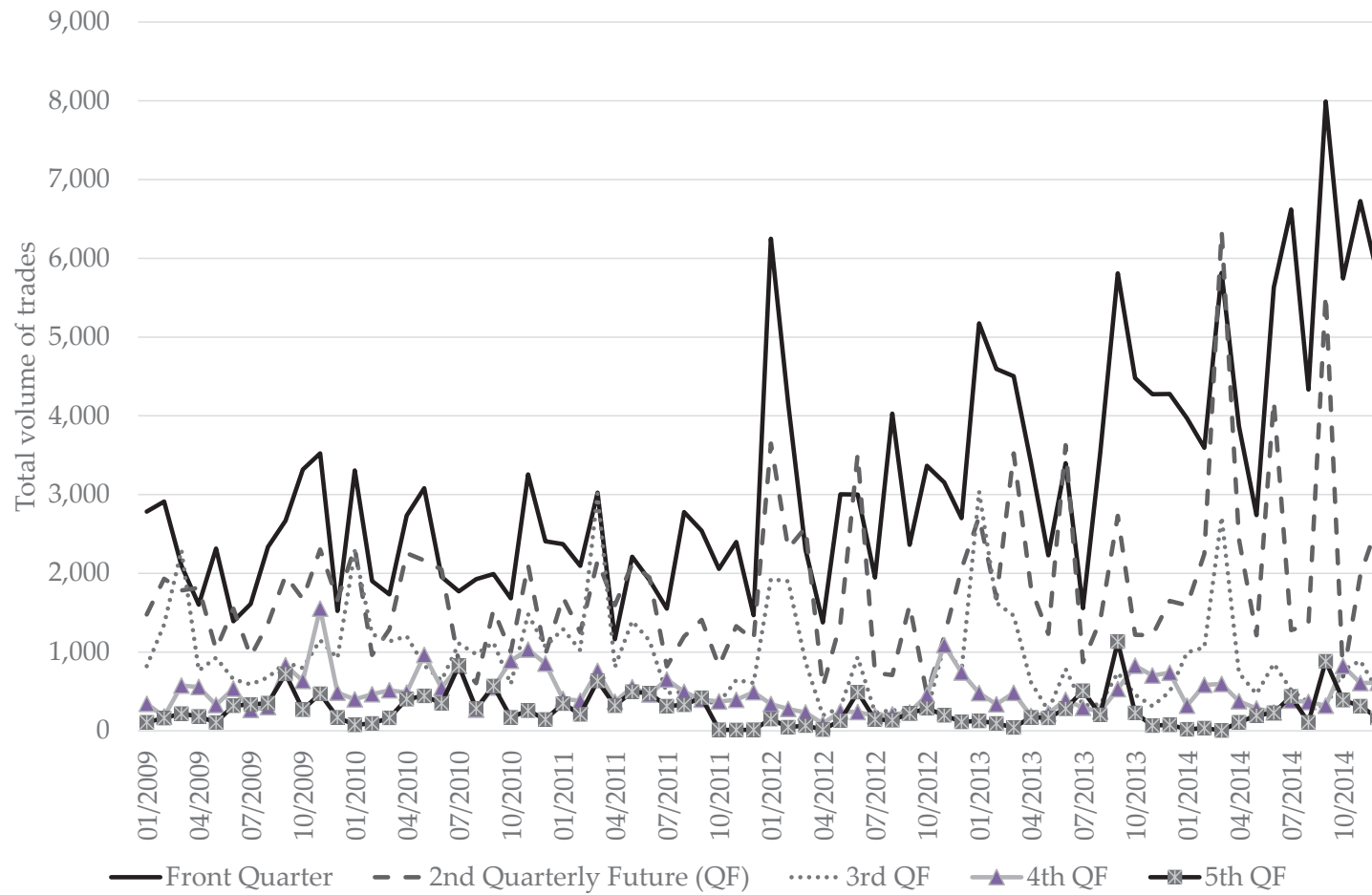


Figure 3: The sum of traded contracts for the quarterly futures, evidence from EPEX, own calculations (source of data [ems.eex.com](http://ems.eex.com)).

## Statistical properties of the noise

- We examined the statistical properties of the noise time-series  $\tilde{\epsilon}_t(x)$

$$\epsilon_t(x) = \sigma(x)\tilde{\epsilon}_t(x) \quad (12)$$

- We found: Overall we conclude that the model residuals are **coloured noise**, with **heavy tails** (leptokurtic distribution) and with a tendency for **conditional volatility**.

| $\tilde{\epsilon}_t(x_k)$ | Stationarity | Autocorrelation $\tilde{\epsilon}_t(x_k)$ | Autocorrelation $\tilde{\epsilon}_t(x_k)^2$ | ARCH/GARCH |
|---------------------------|--------------|-------------------------------------------|---------------------------------------------|------------|
|                           | h            | h1                                        | h1                                          | h2         |
| Q0                        | 0            | 1                                         | 1                                           | 1          |
| Q1                        | 0            | 0                                         | 0                                           | 0          |
| Q2                        | 0            | 1                                         | 1                                           | 1          |
| Q3                        | 0            | 0                                         | 1                                           | 1          |
| Q4                        | 0            | 1                                         | 0                                           | 0          |
| Q5                        | 0            | 1                                         | 1                                           | 1          |
| Q6                        | 0            | 1                                         | 1                                           | 1          |
| Q7                        | 0            | 1                                         | 1                                           | 1          |

Table 1: The time series are selected by quarterly increments (90 days) along the maturity points on one noise curve. Hypotheses tests results, case study 1:  $\Delta x = 1day$ . In column stationarity, if  $h = 0$  we fail to reject the null that series are stationary. For autocorrelation  $h1 = 0$  indicates that there is not enough evidence to suggest that noise time series are autocorrelated. In the last column  $h2 = 1$  indicates that there are significant ARCH effects in the noise time-series.

## Autocorrelation structure of noise time series (squared)

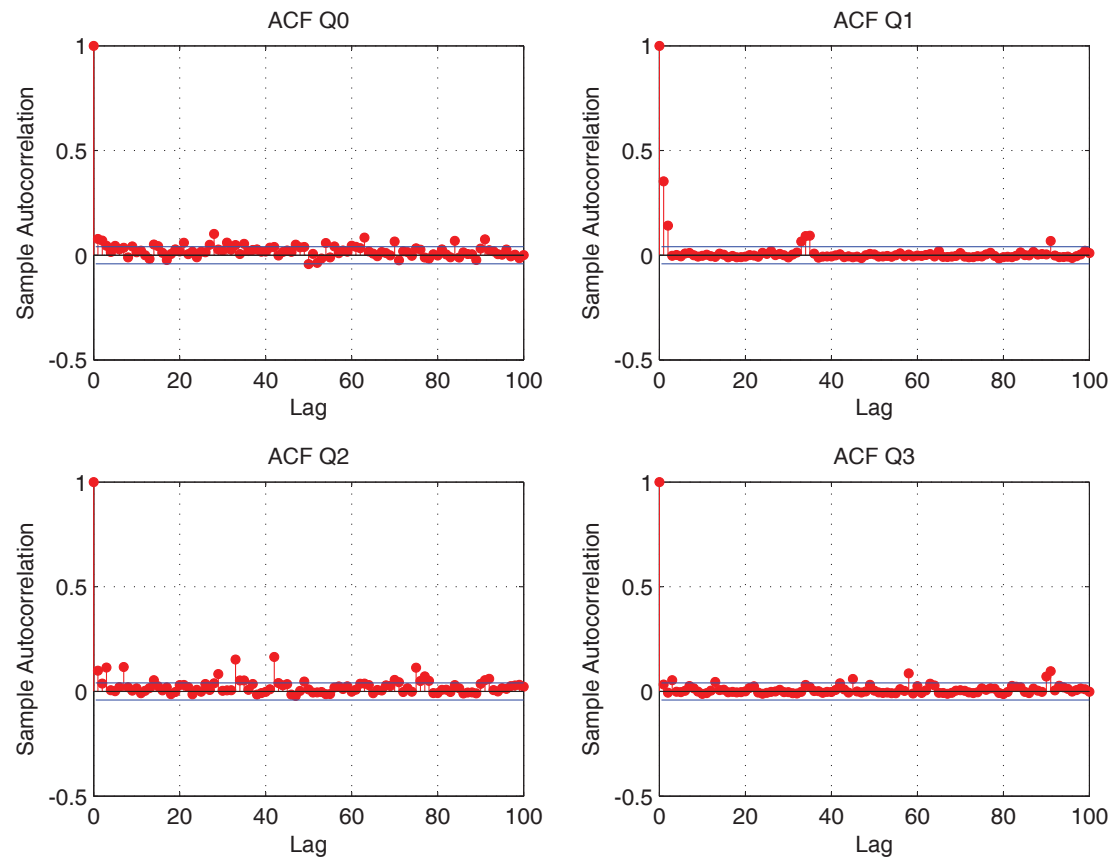
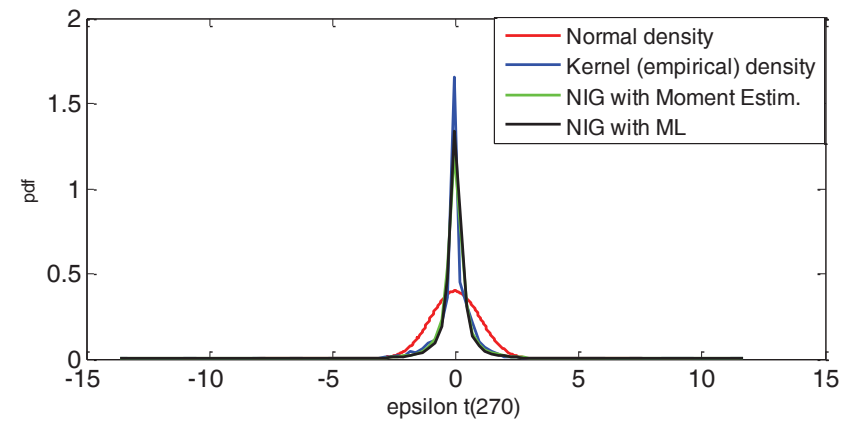
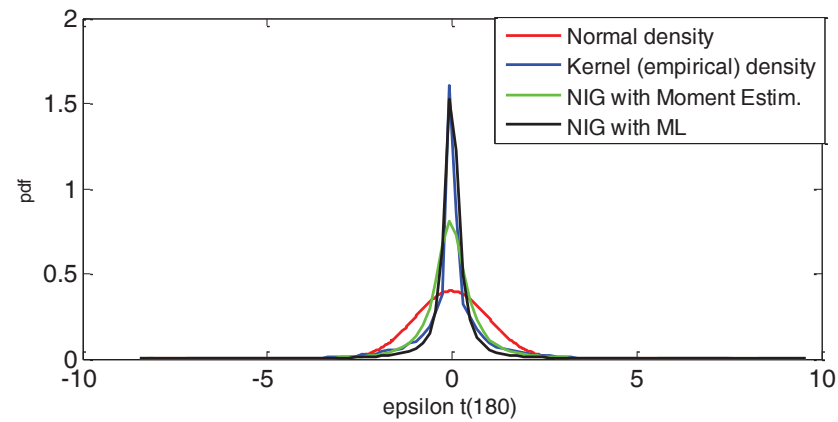
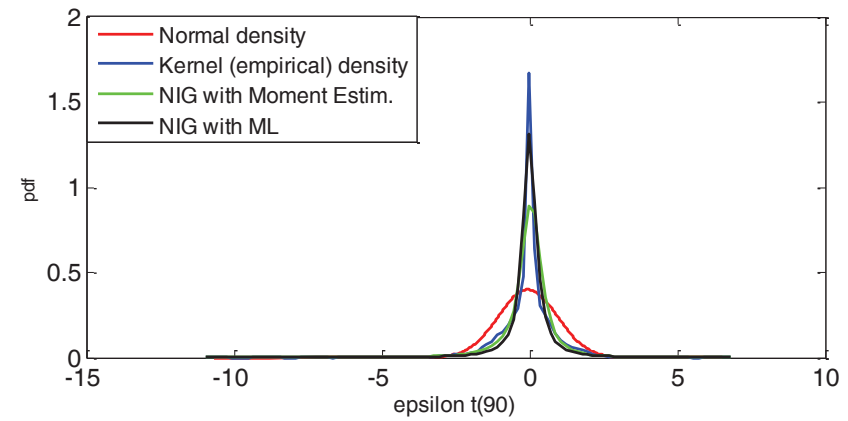
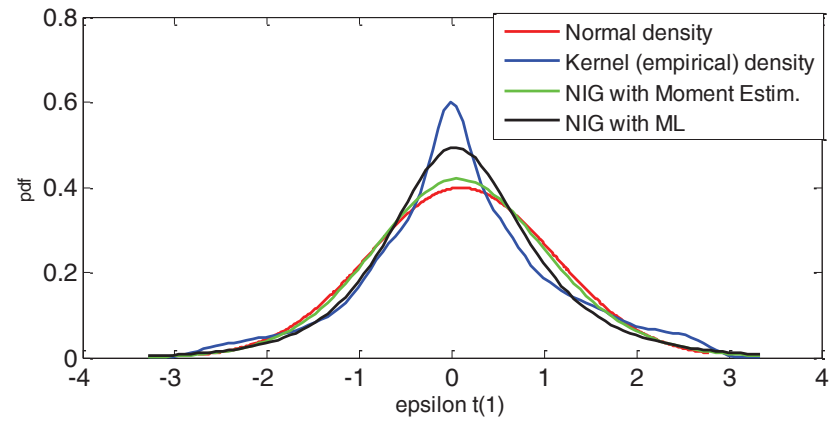


Figure 4: Autocorrelation function in the squared time series of the noise  $\tilde{\epsilon}_t(x_k)^2$ , by taking  $k \in \{1, 90, 180, 270\}$ , case study 1:  $\Delta x = 1 \text{ day}$ .



# Normal Inverse Gaussian (NIG) distribution for coloured noise



## Spatial dependence structure

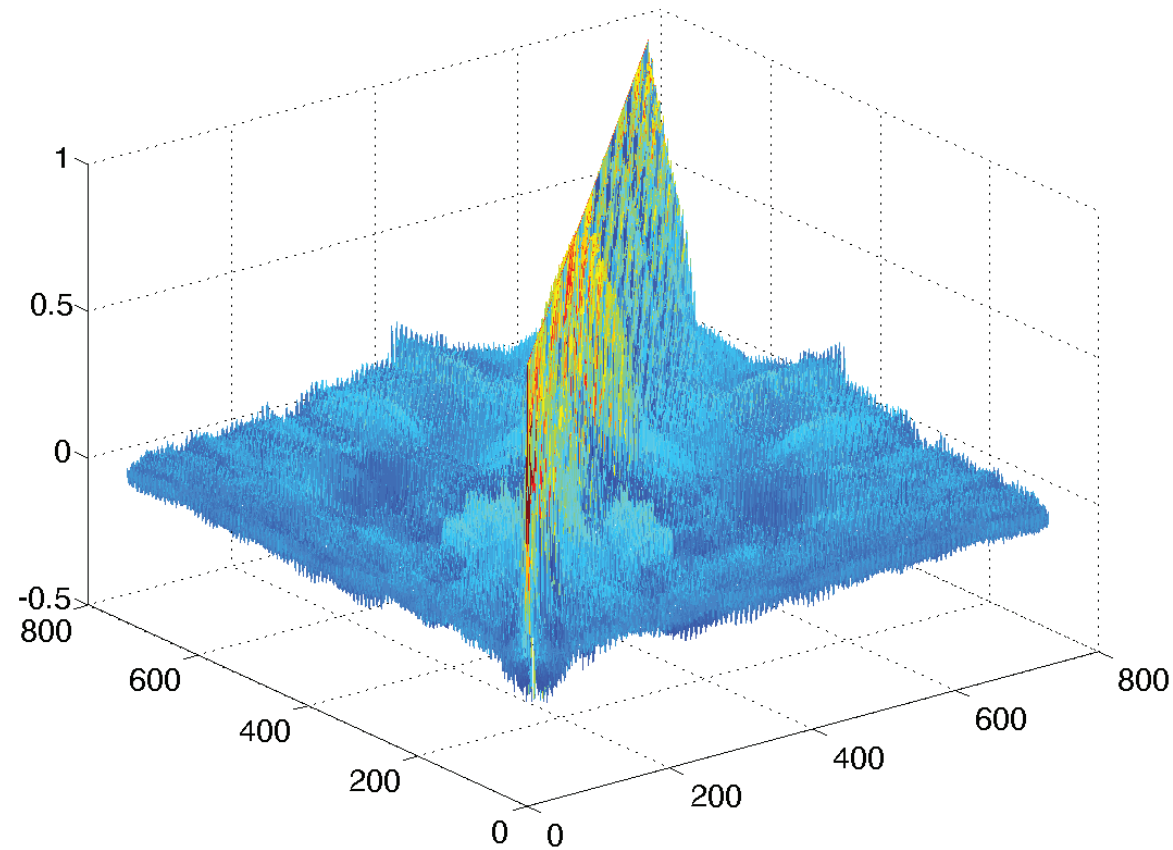


Figure 5: *Correlation matrix with respect to different maturity points along one curve.*

## Revisiting the model

- We have analysed empirically the noise residual  $dW_t(x)$  expressed as  $\epsilon_t(x) = \sigma(x)\tilde{\epsilon}_t(x)$  in a discrete form
- Recover an infinite dimensional model for  $W_t(x)$  based on our findings

$$W_t = \int_0^t \Sigma_s dL_s, \quad (13)$$

where  $s \mapsto \Sigma_s$  is an  $L(\mathcal{U}, \mathcal{H})$ -valued predictable process and  $L$  is a  $\mathcal{U}$ -valued Lévy process with zero mean and finite variance.

- As a first case, we can choose  $\Sigma_s \equiv \Psi$  time-independent:

$$W_{t+\Delta t} - W_t \approx \Psi(L_{t+\Delta t} - L_t) \quad (14)$$

Choose now  $\mathcal{U} = L^2(\mathbb{R})$ , the space of square integrable functions on the real line equipped with the Lebesgue measure, and assume  $\Psi$  is an integral operator on  $L^2(\mathbb{R})$

$$\mathbb{R}_+ \ni x \mapsto \Psi(g)(x) = \int_{\mathbb{R}} \tilde{\sigma}(x, y)g(y) dy \quad (15)$$

- we can further make the approximation  $\Psi(g)(x) \approx \tilde{\sigma}(x, x)g(x)$ , which gives

$$W_{t+\Delta t}(x) - W_t(x) \approx \tilde{\sigma}(x, x)(L_{t+\Delta t}(x) - L_t(x)). \quad (16)$$

## Revisiting the model (cont)

- Recall the spatial correlation structure of  $\tilde{\epsilon}_t(x)$ . This provides the empirical foundation for defining a covariance functional  $\mathcal{Q}$  associated with the Lévy process  $L$ .
- In general, we know that for any  $g, h \in L^2(\mathbb{R})$ ,

$$\mathbb{E}[(L_t, g)_2 (L_t, h)_2] = (\mathcal{Q}g, h)_2$$

where  $(\cdot, \cdot)_2$  denotes the inner product in  $L^2(\mathbb{R})$

$$\mathcal{Q}g(x) = \int_{\mathbb{R}} q(x, y)g(y) dy, \quad (17)$$

- If we assume  $g \in L^2(\mathbb{R})$  to be close to  $\delta_x$ , the Dirac  $\delta$ -function, and likewise,  $h \in L^2(\mathbb{R})$  being close to  $\delta_y$ ,  $(x, y) \in \mathbb{R}^2$ , we find approximately

$$\mathbb{E}[L_t(x)L_t(y)] = q(x, y)$$

- A simple choice resembling to some degree the fast decaying property is  $q(|x - y|) = \exp(-\gamma|x - y|)$  for a constant  $\gamma > 0$ .
- It follows that  $t \mapsto (L_t, g)_2$  is a NIG Lévy process on the real line.

## Conclusion

- We developed a spatio-temporal dynamical arbitrage free model for electricity forward prices based on the Heath-Jarrow-Morton (HJM) approach under Musiela parametrization
- We examined a unique data set of price forward curves derived each day in the market between 2009–2015
- We examined the spatio-temporal structure of our data set
  - **Risk premia:** higher volatility short-term, oscillating around zero; constant volatility on the long-term, turning into negative
  - **Term structure volatility:** Samuelson effect, volatility bumps explained by increased volume of trades
  - **Coloured (leptokurtic) noise** with evidence of conditional volatility
  - **Spatial correlations structure:** decaying fast for short-term maturities; constant (white noise) afterwards with a bump around 1 year
- After explaining the Samuelson effect in the volatility term structure, the residuals are modeled by an infinite dimensional NIG Lévy process, which allows for a natural formulation of a covariance functional.