

# Pricing green financial products

Wolfgang Karl Härdle  
Brenda López Cabrera  
Awdesch Melzer

Ladislaus von Bortkiewicz Chair of Statistics  
Humboldt-Universität zu Berlin  
[lvb.wiwi.hu-berlin.de](http://lvb.wiwi.hu-berlin.de)



**σt**



## Hedging weather risk



# Hedging weather risk

**EDITION: UNITED STATES**

**REUTERS**

Business Markets World Politics Tech Commentary Breakingviews Money Life Pictures Video

"Workable made our recruitment process easier"  
— ZANETA KORPOWSKA - HR SPECIALIST, 10CLOUDS

TRY IT FREE

Markets | Sun Jun 12, 2011 1:00pm EDT

## Insurance-like Product Protects Power Developers from Windless Days

BY MARIA GALLUCCI

[Twitter](#) [Facebook](#) [LinkedIn](#) [Reddit](#) [StumbleUpon](#) [Email](#)

Thanks to new technology, risk management firm Galileo is able to offer wind developers an insurance-like product that helps cover losses on windless days

"Workable takes the headache out of business"

**Nasdaq**

no 75/15 Nasdaq Commodities launches Index for German Wind Power Production

Nasdaq Commodities is pleased to announce the launch of the daily index for German wind power production, the N Renewable Index Wind Germany, NAREX-WIDE.

G+ 0 Like 0 Share 20 Tweet Pin It Share

September 08, 2015 08:00 ET | Source: Nasdaq Commodities

The index will be used as underlying for the Nasdaq Futures contracts for German wind power production that, upon successful testing and regulatory approval, will be launched later this year. This will allow investors to hedge their exposure to the volatility of wind power production.

**RECHARGE**

News Wind Solar Thought Leaders

all in depth analysis opinion europe + africa americas asia + australia offshore technology

## First German wind futures sold on Nasdaq Commodities



**ARTEMIS** [www.artemis.bm](http://www.artemis.bm)

Catastrophe bonds, insurance linked securities, reinsurance capital

Home News Deals & Data MarketView Library Events Categories

**EEX to launch exchange traded wind power derivatives**

by ARTEMIS on MARCH 6, 2015

Share 10

European Energy Exchange AG, the EEX, is planning to launch exchange traded wind power derivatives and futures as a response to the "energy turnaround" which sees renewables increasing their share of global energy production.

Weather derivatives and weather hedging tools are going to play an increasingly important role as the energy markets turn towards renewables. Germany is one of the energy markets that is shifting towards renewables at the fastest rate and the EEX, which is majority owned by Deutsche Boerse's derivatives exchange Eurex, is keen to be at the forefront.

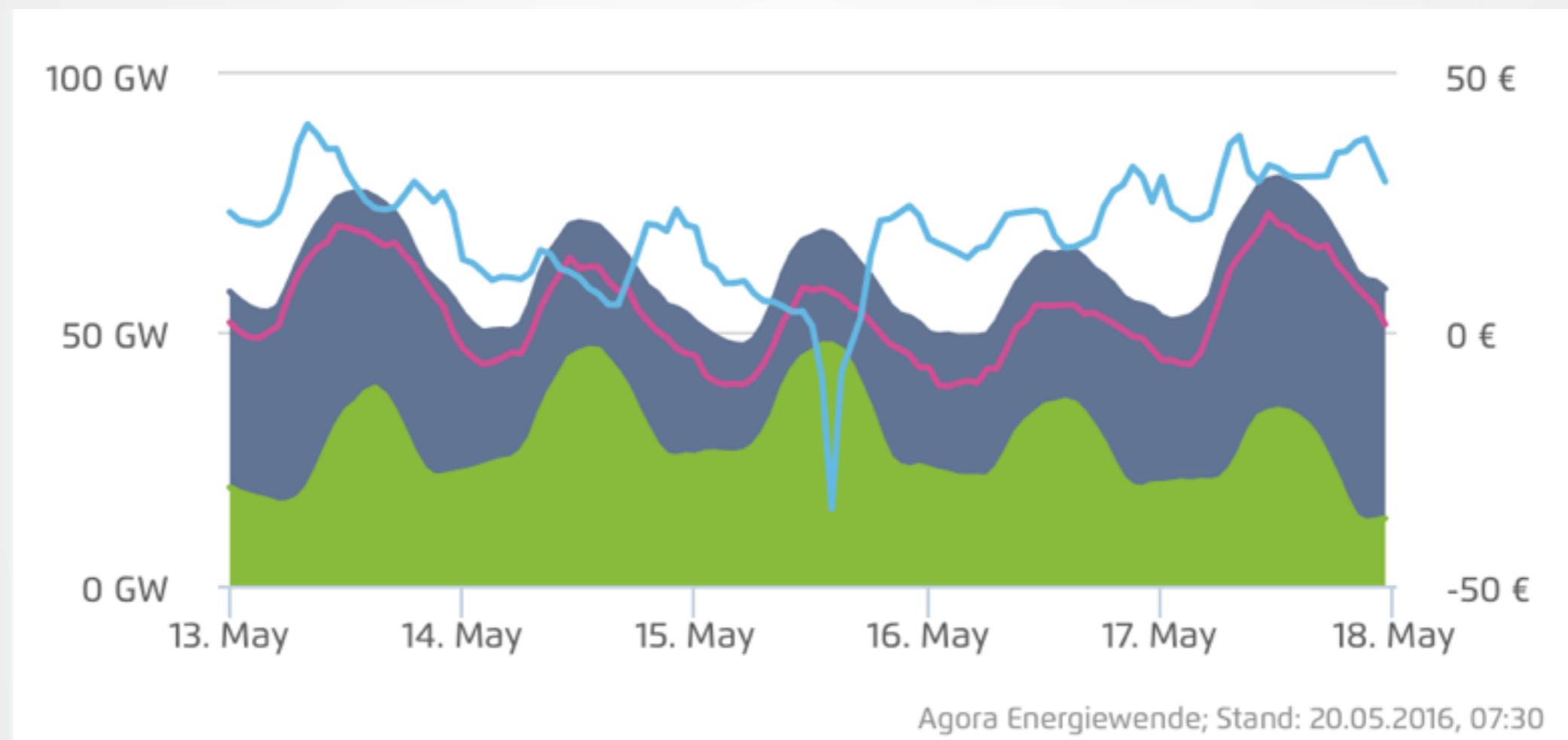


## Weather risk in energy production

- Renewables become dominating energy source
- Energy output highly dependent on weather conditions
  - “Lack of wind” phenomenon
  - Sudden wind speed changes: strong power drop
  - Unsteady wind direction: zero wind power
  - Cloud coverage over one solar panel affects the panel output of an entire farm excessively



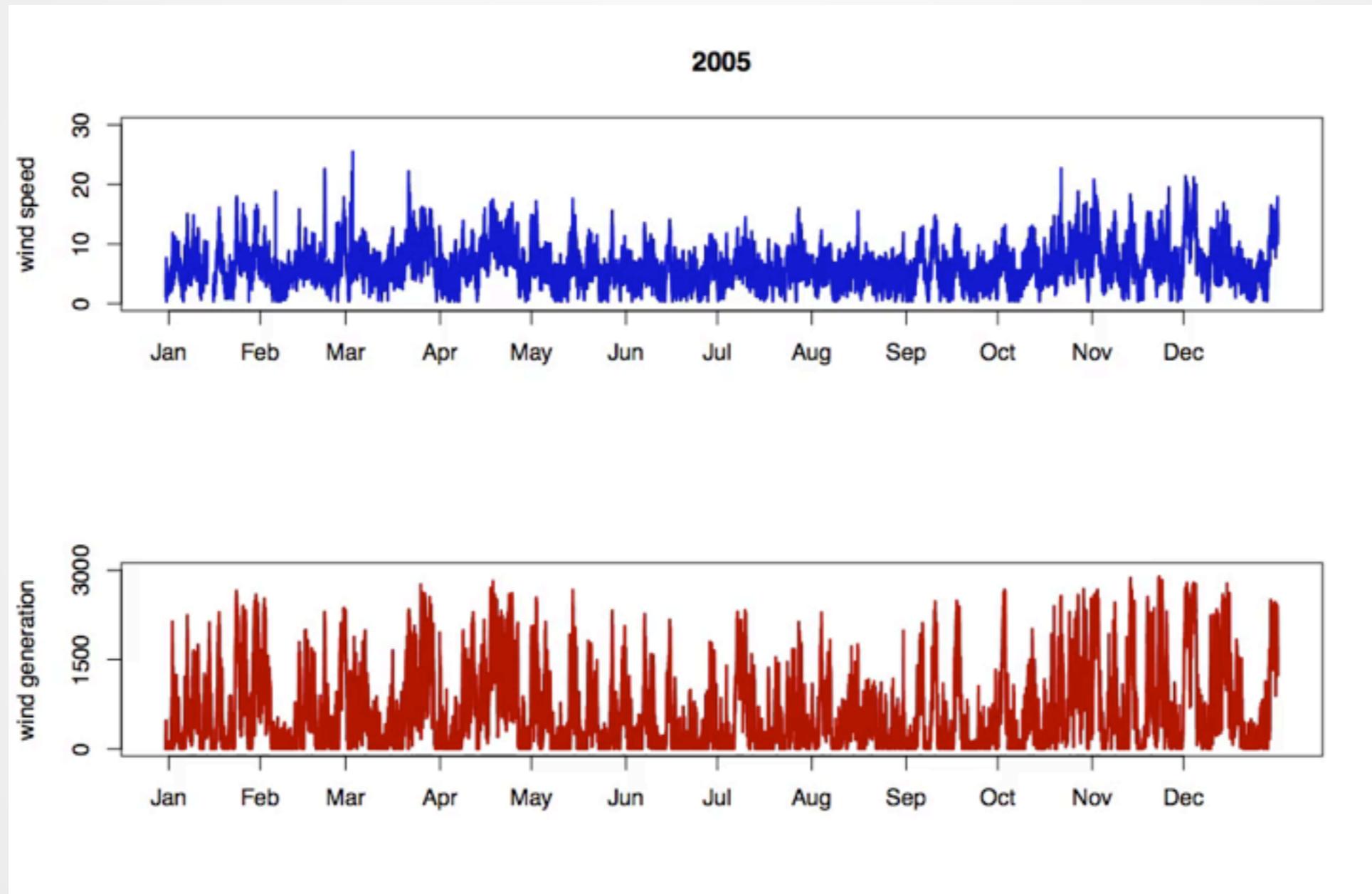
Pentecost 2016 in Germany:  
renewables cover over 80% of electricity demand -  
prices drop below zero



Electricity price; electricity demand; conventional power generation; renewable power generation



## Having wind ≠ producing energy



## Green financial products

Hedge weather related risk exposures on energy production due to climate volatility

- Payments based on weather related measurements
- Applicable to any renewable energy project
  - biomass, wave, tidal, hydropower, solar energy
  - hedging against “lack of wind”
  - prices below zero (post-feed-in)
- Underlying: indices on wind speed, sun duration, cloud coverage, etc.



## Wind futures at European Energy eXchange (EEX)

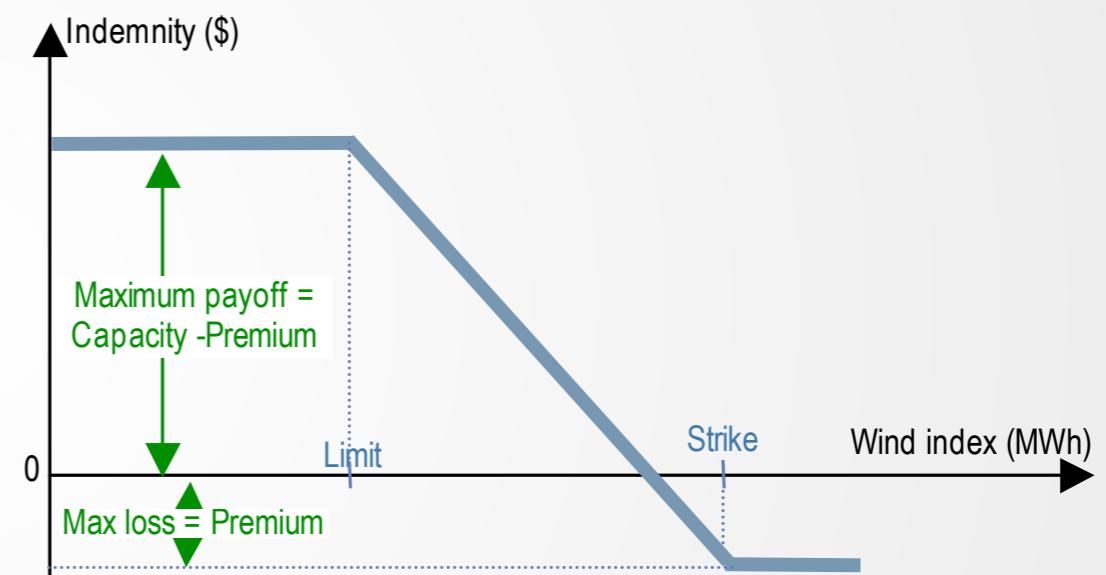
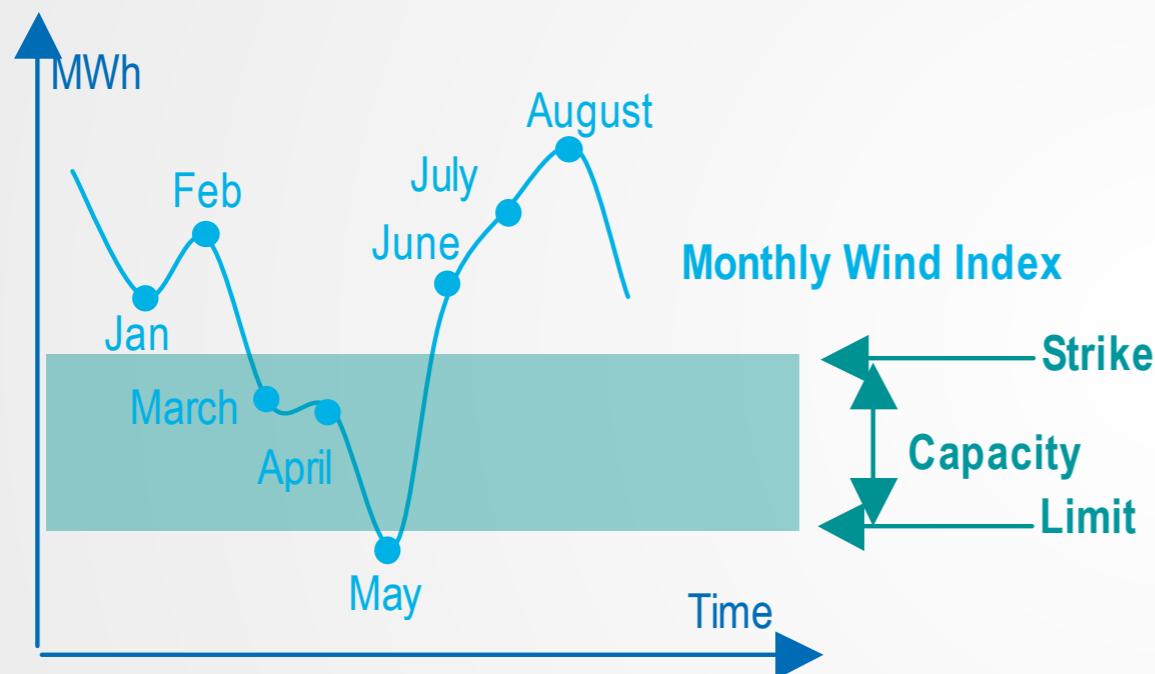
- **Contract:** A contract settling against the expected on-site power production of future delivery periods
- **Underlying:** Average wind load factor per contract period;  
alternatives:
  - wind speed, wind direction, wind duration indices

Example: Cumulative Average Wind Speed index:

$$CAWS(\tau_1; \tau_2) = \int_{\tau_1}^{\tau_2} W(s) ds$$



## Wind futures mechanism



Left: Wind futures mechanism; Right: payoff profile



# Weather Derivatives at Chicago Mercantile Exchange

CME products

- $\text{HDD}(\tau_1, \tau_2) = \int_{\tau_1}^{\tau_2} \max(18^\circ\text{C} - T_t, 0) dt$
- $\text{CDD}(\tau_1, \tau_2) = \int_{\tau_1}^{\tau_2} \max(T_t - 18^\circ\text{C}, 0) dt$
- $\text{CAT}(\tau_1, \tau_2) = \int_{\tau_1}^{\tau_2} T_t dt$ , where  $T_t = \frac{T_{t,\max} + T_{t,\min}}{2}$
- $\text{AAT}(\tau_1, \tau_2) = \int_{\tau_1}^{\tau_2} \tilde{T}_t dt$ , where  $\tilde{T}_t = \frac{1}{24} \int_1^{24} T_{t,i} dt_i$  and  $T_{t,i}$  denotes the temperature of hour  $t_i$ , (also referred to as C24AT index).



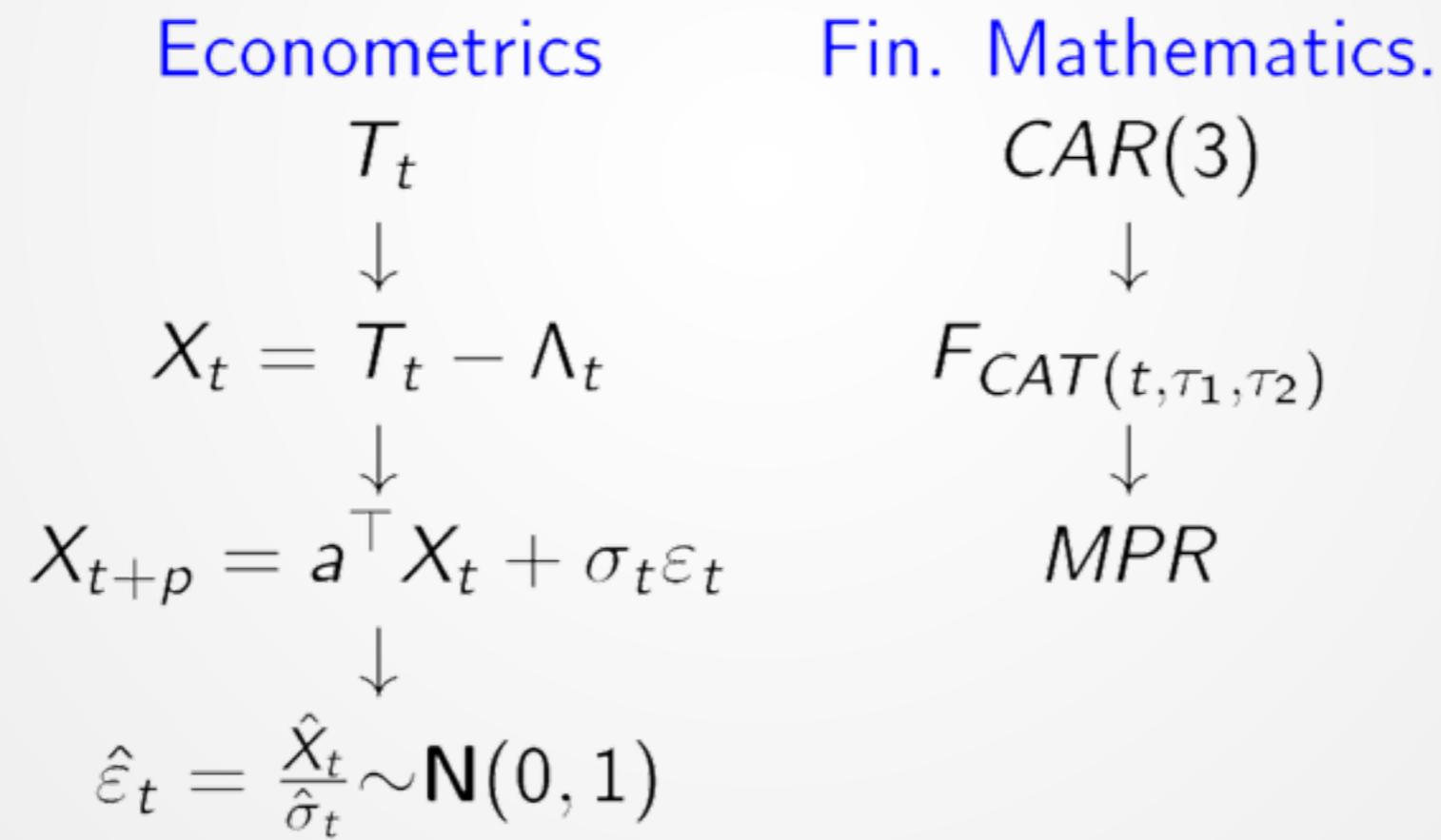
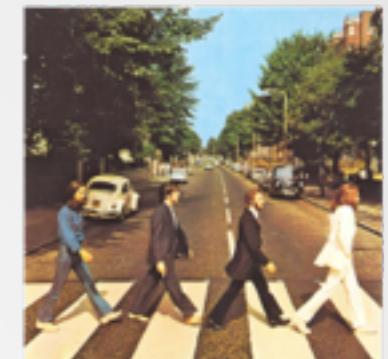
## Research questions

- How to model weather dynamics?
- How to estimate market price of risk?
- How to create Gaussian stochastic drivers?





# The FEB Four Algorithm



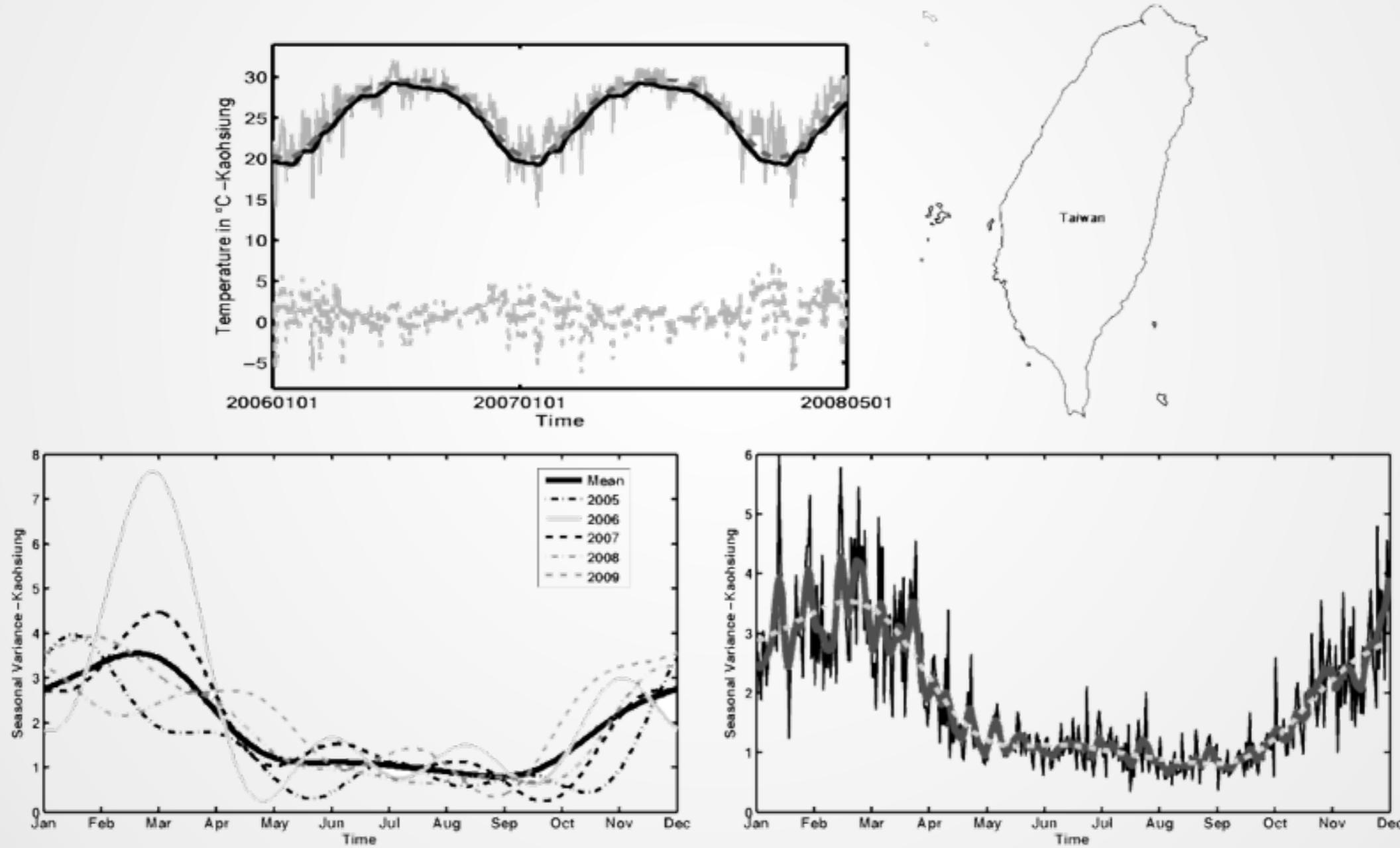
---

# Outline

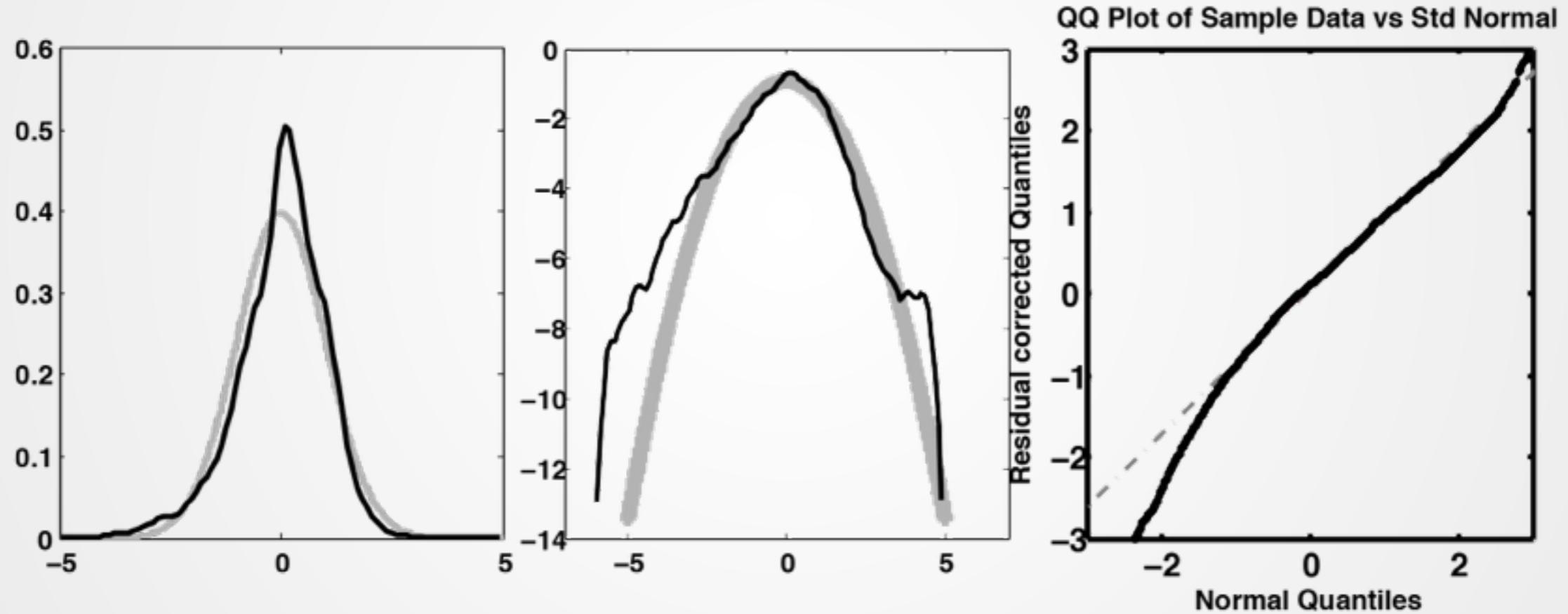
1. Motivation
2. Econometric methods and normality
3. Stochastic pricing of WD
4. Summary



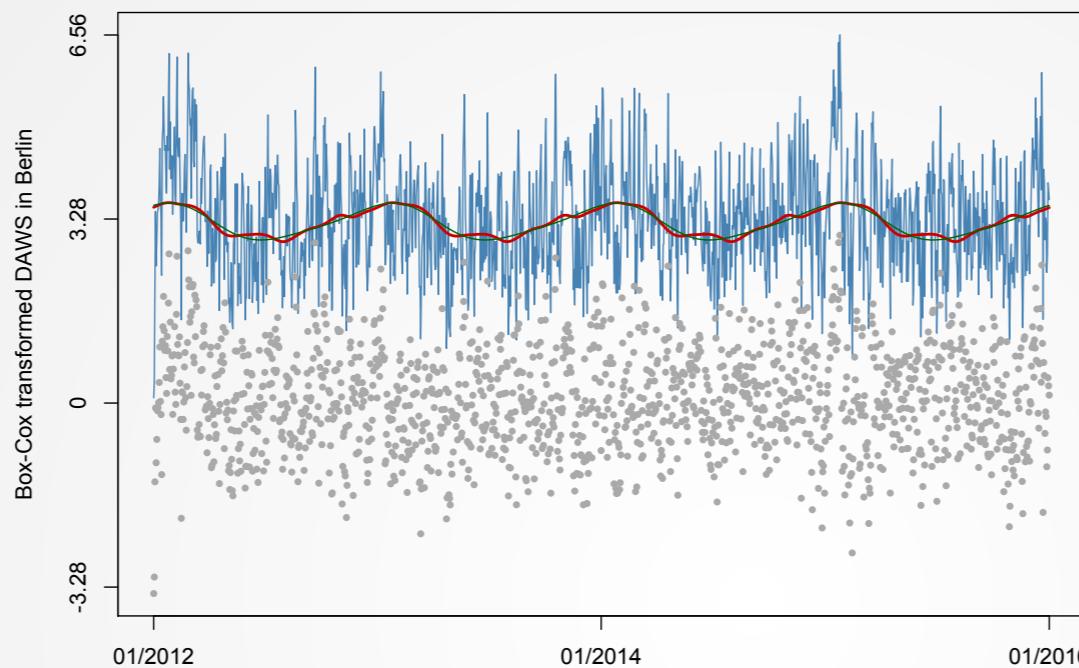
## Stylised facts in temperature



## Stylised facts in temperature



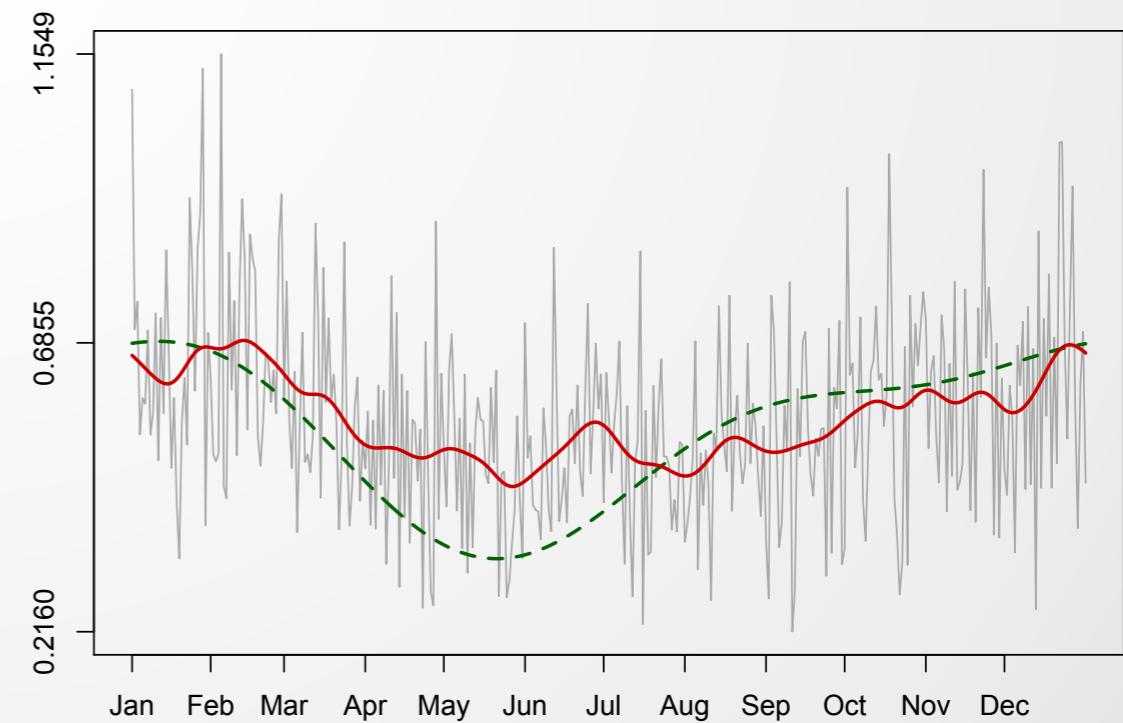
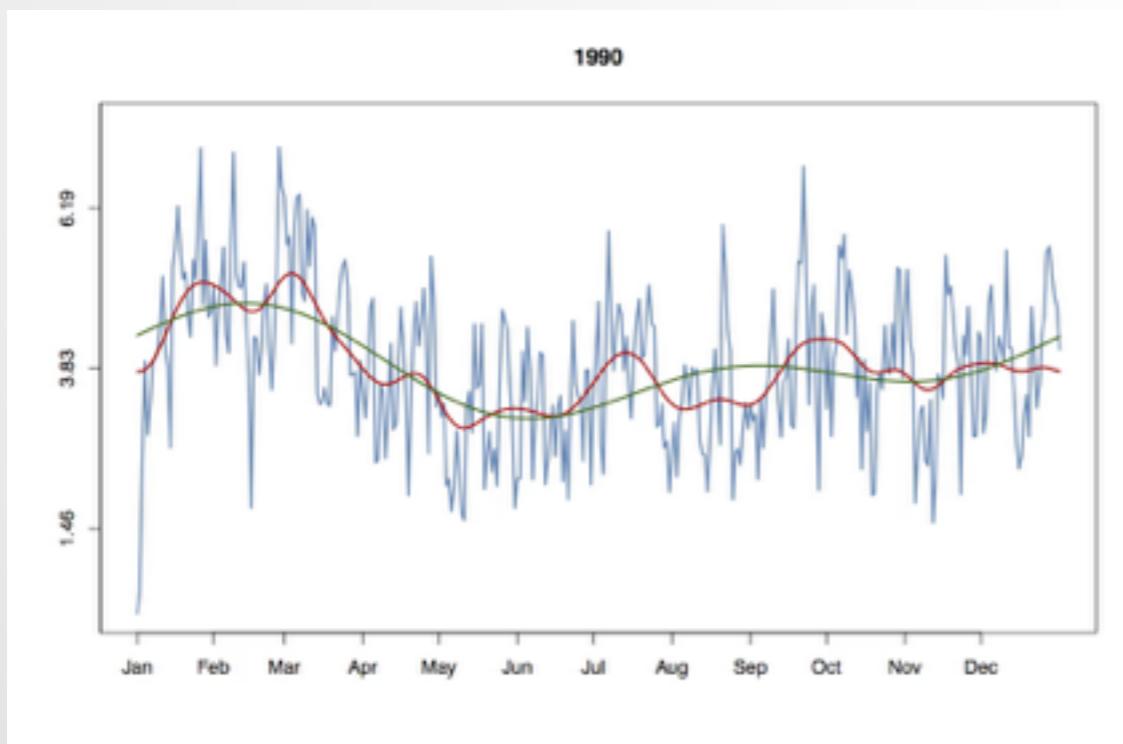
## Stylised facts in wind



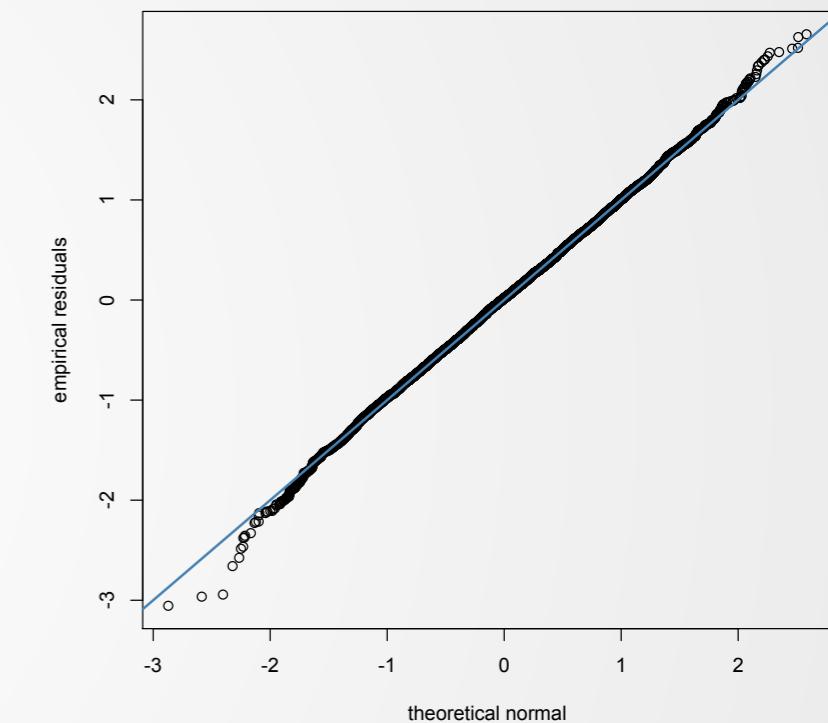
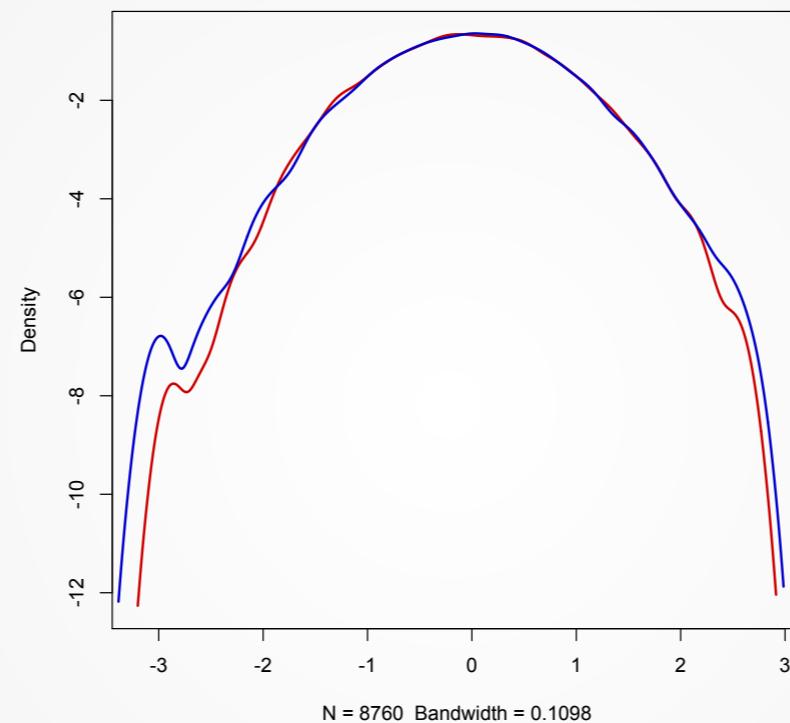
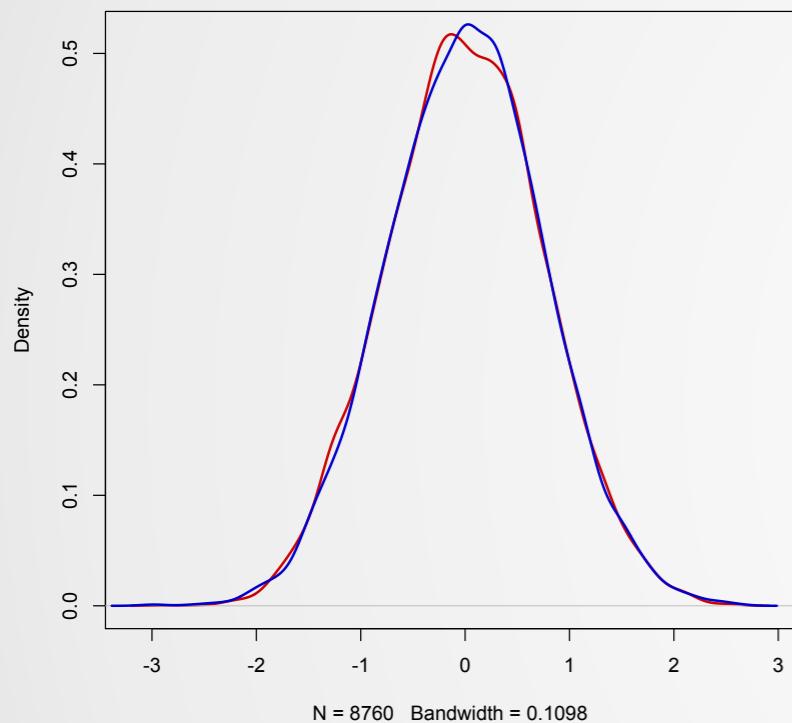
Box-Cox transformation

$$\tilde{W}_t = \frac{W_t^\lambda - 1}{\lambda}$$

$$\hat{\lambda}_{norm} = 0.375$$



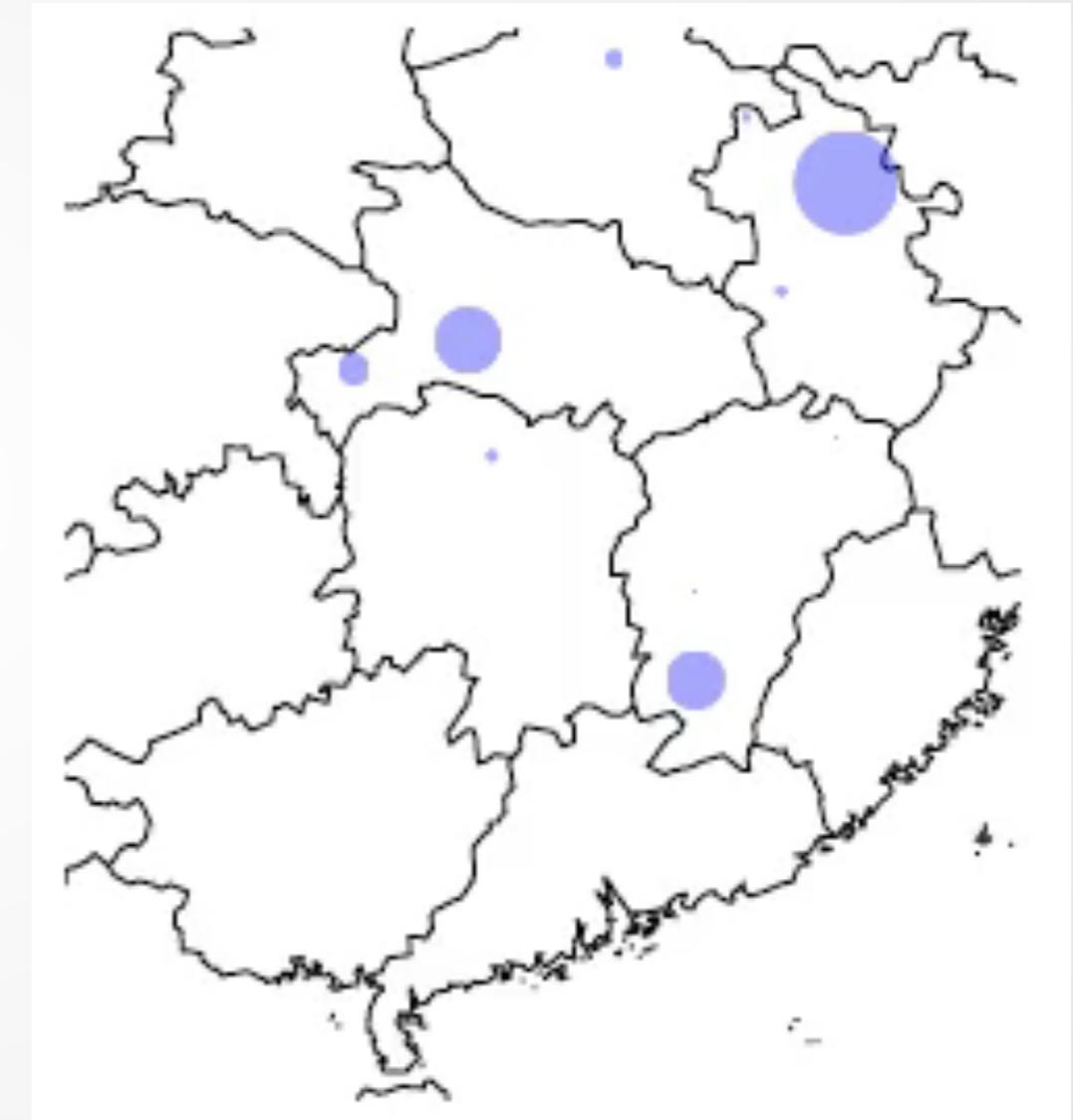
## Stylised facts in wind



 PGFPwiforpricing



## Other areas: pricing rain



Härdle and Osipenko (2016)

Pricing Chinese rain



# Weather Derivatives

## CME products

- $\text{HDD}(\tau_1, \tau_2) = \int_{\tau_1}^{\tau_2} \max(18^\circ\text{C} - T_t, 0) dt$
- $\text{CDD}(\tau_1, \tau_2) = \int_{\tau_1}^{\tau_2} \max(T_t - 18^\circ\text{C}, 0) dt$
- $\text{CAT}(\tau_1, \tau_2) = \int_{\tau_1}^{\tau_2} T_t dt$ , where  $T_t = \frac{T_{t,\max} + T_{t,\min}}{2}$
- $\text{AAT}(\tau_1, \tau_2) = \int_{\tau_1}^{\tau_2} \tilde{T}_t dt$ , where  $\tilde{T}_t = \frac{1}{24} \int_1^{24} T_{t,i} dt_i$  and  $T_{t,i}$  denotes the temperature of hour  $t_i$ , (also referred to as C24AT index).



## Stochastic pricing

Ornstein-Uhlenbeck process  $\mathbf{X}_t \in \mathbb{R}^p$ :

$$d\mathbf{X}_t = \mathbf{A}\mathbf{X}_t dt + \mathbf{e}_p \sigma_t dB_t$$

$\mathbf{e}_k$ :  $k$ th unit vector in  $\mathbb{R}^p$  for  $k = 1, \dots, p$ ,  $\sigma_t > 0$ ,  $\mathbf{A}$ :  $(p \times p)$ -matrix

$$\mathbf{A} = \begin{pmatrix} 0 & 1 & 0 & \dots & 0 \\ 0 & 0 & 1 & \dots & 0 \\ \vdots & & \ddots & & \vdots \\ 0 & \dots & \dots & 0 & 1 \\ -\alpha_p & -\alpha_{p-1} & \dots & & -\alpha_1 \end{pmatrix}$$

Proof



## CAT Futures

For  $0 \leq t \leq \tau_1 < \tau_2$ :

$$\begin{aligned}
 F_{CAT(t, \tau_1, \tau_2)} &= E^{Q_\lambda} \left[ \int_{\tau_1}^{\tau_2} T_s ds | \mathcal{F}_t \right] \\
 &= \int_{\tau_1}^{\tau_2} \Lambda_u du + \mathbf{a}_{t, \tau_1, \tau_2} \mathbf{X}_t + \int_t^{\tau_1} \lambda_u \sigma_u \mathbf{a}_{t, \tau_1, \tau_2} \mathbf{e}_p du \\
 &\quad + \int_{\tau_1}^{\tau_2} \lambda_u \sigma_u \mathbf{e}_1^\top \mathbf{A}^{-1} [\exp \{ \mathbf{A}(\tau_2 - u) \} - I_p] \mathbf{e}_p du \quad (2)
 \end{aligned}$$

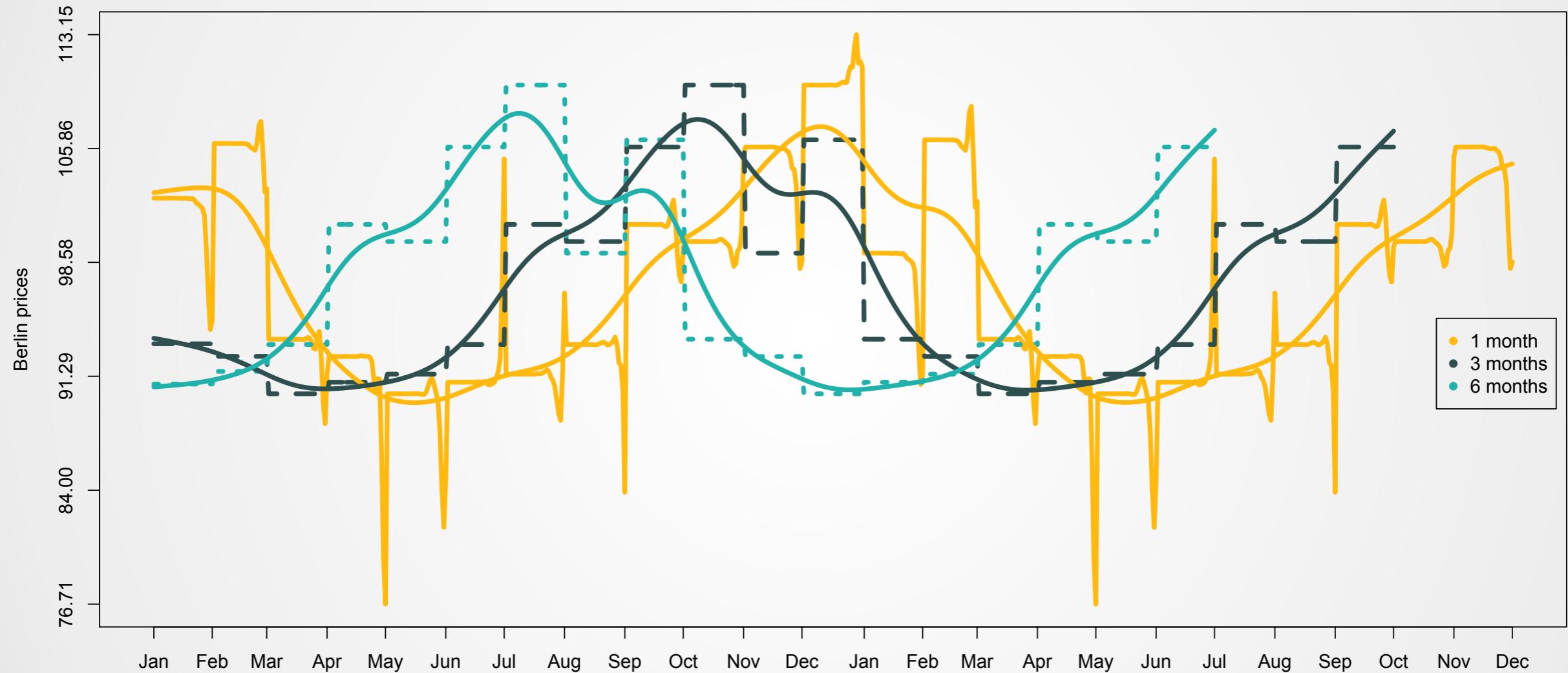
with  $\mathbf{a}_{t, \tau_1, \tau_2} = \mathbf{e}_1^\top \mathbf{A}^{-1} [\exp \{ \mathbf{A}(\tau_2 - t) \} - \exp \{ \mathbf{A}(\tau_1 - t) \}]$ ,  $I_p : p \times p$   
identity matrix

Benth et al. (2007)

 fCAWSpricing



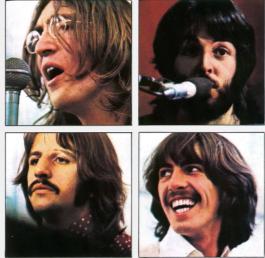
## CAWS Futures



Estimated wind future prices for contract length of 1, 3 and 6 months, in Berlin 2012-2013



## Conclusion & further research

-  - procedure performs well & applicable to many subjects
- MPR estimation in wind energy: Nasdaq, EEX prices required
- Adaptive optimality for bandwidth selection and transformation
- Extend to spatial wind pricing



## References

- F.E. Benth and J.S. Benth and S. Koekbakker  
*Putting a Price on Temperature*  
Scandinavian Journal of Statistics 34: 746-767, 2007
- F.E. Benth and W.K. Härdle and B.López Cabrera  
*Pricing of Asian Temperature Risk*  
To appear in Statistics Tools of Finance and Insurance,  
W.K. Härdle, R. Weron editors, 2nd. edition, 2011
- P.J. Brockwell  
*Continuous-time ARMA Processes*  
Handbook of Statistics 19: 248-276, 2001



- W.K. Härdle and M. Osipenko  
*Pricing Chinese Rain*  
WHERE????
- W.K. Härdle and B. López Cabrera  
*Implied Market Price of Weather Risk*  
Journal of Applied Mathematical Finance, 2010
- U. Horst and M. Müller  
*On the Spanning Property of Risk Bonds Priced by Equilibrium*  
Mathematics of Operations Research 4: 784-807, 2007
- W.K. Härdle, J. Franke, C.M. Hafner  
*Statistics of Financial Markets: 3rd edition*  
Springer Verlag, Heidelberg, 2011



# Pricing green financial products

Wolfgang Karl Härdle  
Brenda López Cabrera  
Awdesch Melzer



Ladislaus von Bortkiewicz Chair of Statistics  
Humboldt-Universität zu Berlin  
[lvb.wiwi.hu-berlin.de](http://lvb.wiwi.hu-berlin.de)



**σt**



$X_t$  can be written as a Continuous-time AR(p) (CAR(p)):

For  $p = 1$ ,

$$dX_{1t} = -\alpha_1 X_{1t} dt + \sigma_t dB_t$$

For  $p = 2$ ,

$$\begin{aligned} X_{1(t+2)} &\approx (2 - \alpha_1)X_{1(t+1)} \\ &+ (\alpha_1 - \alpha_2 - 1)X_{1t} + \sigma_t(B_{t-1} - B_t) \end{aligned}$$

For  $p = 3$ ,

$$\begin{aligned} X_{1(t+3)} &\approx (3 - \alpha_1)X_{1(t+2)} + (2\alpha_1 - \alpha_2 - 3)X_{1(t+1)} \\ &+ (-\alpha_1 + \alpha_2 - \alpha_3 + 1)X_{1t} + \sigma_t(B_{t-1} - B_t) \end{aligned}$$



## Proof $CAR(3) \approx AR(3)$

Let

$$A = \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ -\alpha_3 & -\alpha_2 & -\alpha_1 \end{pmatrix}$$

- use  $B_{t+1} - B_t = \varepsilon_t$
- assume a time step of length one  $dt = 1$
- substitute iteratively into  $X_1$  dynamics



Proof  $CAR(3) \approx AR(3)$ :

$$\begin{aligned}
 X_{1(t+1)} - X_{1(t)} &= X_{2(t)} dt \\
 X_{2(t+1)} - X_{2(t)} &= X_{3(t)} dt \\
 X_{3(t+1)} - X_{3(t)} &= -\alpha_1 X_{1(t)} dt - \alpha_2 X_{2(t)} dt - \alpha_3 X_{3(t)} dt + \sigma_t \varepsilon_t \\
 X_{1(t+2)} - X_{1(t+1)} &= X_{2(t+1)} dt \\
 X_{2(t+2)} - X_{2(t+1)} &= X_{3(t+1)} dt \\
 X_{3(t+2)} - X_{3(t+1)} &= -\alpha_1 X_{1(t+1)} dt - \alpha_2 X_{2(t+1)} dt \\
 &\quad - \alpha_3 X_{3(t+1)} dt + \sigma_{t+1} \varepsilon_{t+1} \\
 X_{1(t+3)} - X_{1(t+2)} &= X_{2(t+2)} dt \\
 X_{2(t+3)} - X_{2(t+2)} &= X_{3(t+2)} dt \\
 X_{3(t+3)} - X_{3(t+2)} &= -\alpha_1 X_{1(t+2)} dt - \alpha_2 X_{2(t+2)} dt \\
 &\quad - \alpha_3 X_{3(t+2)} dt + \sigma_{t+2} \varepsilon_{t+2}
 \end{aligned}$$

[Return](#)



## Seasonal variance: LLE - mirroring observations

To avoid the boundary problem, use mirrored observations:

Assume  $h_K < 365/2$ , then the observations look like

$\hat{\varepsilon}_{-364}^2, \hat{\varepsilon}_{-363}^2, \dots, \hat{\varepsilon}_0^2, \hat{\varepsilon}_1^2, \dots, \hat{\varepsilon}_{730}^2$ , where

$$\hat{\varepsilon}_t^2 \stackrel{\text{def}}{=} \hat{\varepsilon}_{365+t}^2, -364 \leq t \leq 0$$

$$\hat{\varepsilon}_t^2 \stackrel{\text{def}}{=} \hat{\varepsilon}_{t-365}^2, 366 \leq t \leq 730$$

