Assessing the Impact of Wind Energy on Electricity Prices in Germany

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Electricity spot prices

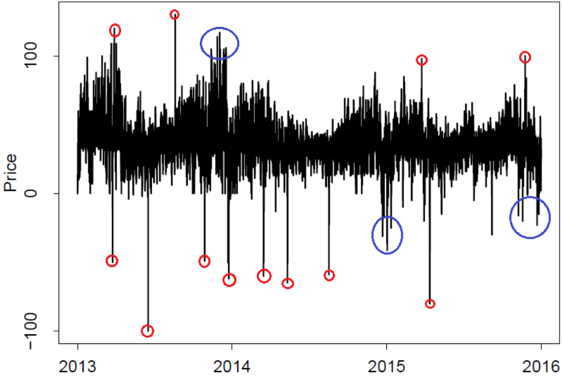

Figure 1: Hourly electricity spot prices from EEX

Electricity spot prices

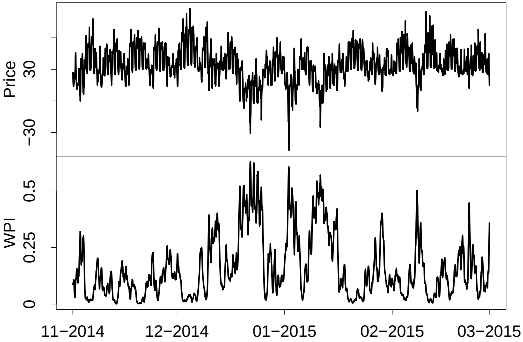

Figure 2: Hourly electricity spot prices from EEX and Wind Penetration Index (WPI)

German Electricity Market

- Limited storability
- Inelastic demand
- Feed-in guarantee of renewable energy
- Day-ahead single price auction
- Merit order Merit-Order

- Merit order effect (Würzburg et al., 2013)

Challenges

- Seasonality
- Mean reversion
- High volatility
- Jumps
- Effect of renewables
- Uncertainty about states

Objectives

- Modeling hourly spot prices
  - Assess impact of wind power generation
  - Capture spikes
- Day-ahead forecasting
  - Evaluate against benchmark models

Methodology

- Markov-switching model
  - States with different underlying stochastic processes
  - Frequent changes at random points in time between states
- Time-varying switching probabilities
  - Dependence on wind power generation

Outline

1. Motivation ✓
2. Data
3. Methodology
4. Empirical results
5. Conclusion

Data

- Hourly data on
  - Total load (ENTSO-E)
  - Day-ahead spot price (Bloomberg)
  - Day-ahead forecasts of wind power production (TSOs)
- from January 2013 to December 2015
- Subsample of two years for in-sample fitting

Data

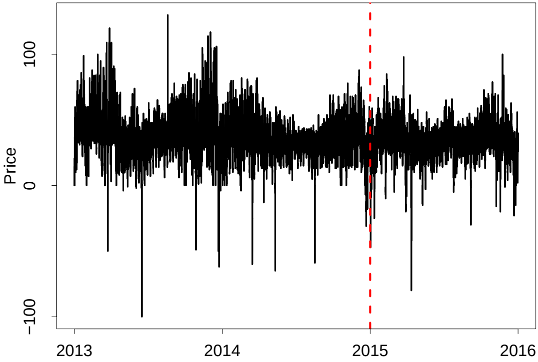

Figure 3: Hourly electricity spot prices from EEX

Statistical Model for Spot Prices

$$\widetilde{\pi}_t = \pi_t + \Lambda_t, \quad t = 1, \dots, n$$

where

- $\widetilde{\pi}_t$ - observed price
- π_t - stochastic component
- Λ_t - deterministic seasonal component

Deterministic Seasonal Component

$$\Lambda_{s,k} = a_s + b_s k + \sum_{i=1}^{11} c_{i,s} m_{i,k} + \sum_{j=1}^{6} d_{j,s} w_{j,k} + e_s h_k$$

where

- $s = 1, \ldots, 24, \quad k = 1, \ldots K$
- $m_{i,t}$ - dummies for months
- $d_{j,t}$ - dummies for weekdays
- h_t - dummy for public holidays
- a, b, c_i, d_i, e - parameters to be estimated

Wind Penetration Index

- Proportion of electricity produced from wind

$$WPI_t = \frac{V_t}{D_t}$$

where

- V_t - day-ahead forecast of wind power production at hour t
- D_t - total load at hour t

- Wind Penetration Indicator

$$d_t := \begin{cases} 0 & \text{if } WP_t \leq Q_{0.75}(WP_t) \\ 1 & \text{if } WP_t \geq Q_{0.75}(WP_t) \end{cases}$$

Data

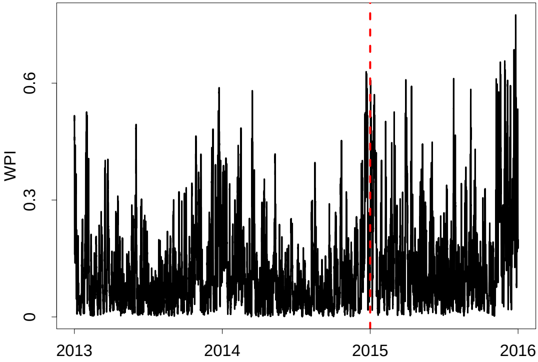

Figure 4: Wind Penetration Index (WPI)

Two Regime Markov-Switching Model

- For a set of regimes S={1,2}

$$\pi_t = \begin{cases} f_1(Z_t;\theta) & \text{if } s_t = 1 \\ f_2(Z_t;\theta) & \text{if } s_t = 2 \end{cases}$$

where

- f_{s_t} - underlying process
- Z_t - explanatory variables
- θ - parameters

Two Regime Markov-Switching Model

- States s_t are unobserved
- Switches are governed by first order Markov Chain

$$\mathrm{P}(s_t = j | s_{t-1} = i, s_{t-2} = k, \ldots) = \mathrm{P}(s_t = j | s_{t-1} = i) = p_{ij}$$

- Transition probabilities

$$\mathbf{P} = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix} = \begin{pmatrix} p_{11} & 1 - p_{11} \\ 1 - p_{22} & p_{22} \end{pmatrix}$$

Two Regime Markov-Switching Model for electricity

$$\pi_t = \begin{cases} \pi_{1,t} = \phi_0 + \phi_1 \pi_{t-1} + \varepsilon_t & \text{if } s_t = 1 \text{ (base regime)} \\ \pi_{2,t} \sim \mathrm{N}(\mu_2, \sigma_2^2) & \text{if } s_t = 2 \text{ (jump regime)} \end{cases}$$

- Base regime: AR(1)-process
  - $\varepsilon_t \sim \mathrm{N}(0, \sigma_1)$
- Jump regime: Gaussian distribution
- $\phi_0, \phi_1, \sigma_1, \mu_2, \sigma_2$ - parameters to be estimated

Time-Varying Probabilities

$$\mathbf{P}_t = \begin{pmatrix} p_t^{11} & 1-p_t^{11} \\ 1-p_t^{22} & p_t^{22} \end{pmatrix} = \begin{pmatrix} \frac{e^{x_t\beta_1}}{1+e^{x_t\beta_1}} & 1-\frac{e^{x_t\beta_1}}{1+e^{x_t\beta_1}} \\ 1-\frac{e^{x_t\beta_2}}{1+e^{x_t\beta_2}} & \frac{e^{x_t\beta_2}}{1+e^{x_t\beta_2}} \end{pmatrix}$$

For $x_t = d_t$

$$\mathbf{P}_t = \begin{cases} \begin{pmatrix} \frac{e^{\beta_{10}}}{1+e^{\beta_{10}}} & \frac{1}{1+e^{\beta_{10}}} \\ \frac{1}{1+e^{\beta_{20}}} & \frac{e^{\beta_{20}}}{1+e^{\beta_{20}}} \end{pmatrix} & \text{if } d_t = 0 \\ \begin{pmatrix} \frac{e^{\beta_{10}+\beta_{11}}}{1+e^{\beta_{10}+\beta_{11}}} & \frac{1}{1+e^{\beta_{10}+\beta_{11}}} \\ \frac{1}{1+e^{\beta_{20}+\beta_{21}}} & \frac{e^{\beta_{20}+\beta_{21}}}{1+e^{\beta_{20}+\beta_{21}}} \end{pmatrix} & \text{if } d_t = 1 \end{cases}$$

In-sample Estimates

	ϕ_0	ϕ_1	σ_1	μ_2	σ_2
Constant	0.32	0.83	5.98	−7.26	25.53
Time-varying	0.87	0.81	5.73	−8.37	13.28

Table 1: Parameter Estimates

Estimated Transition Probabilities

- Constant transition probabilities

$$\mathbf{P} = \begin{pmatrix} 0.98 & 0.02 \\ 0.26 & 0.74 \end{pmatrix}$$

- Time-varying transition probabilities

$$\mathbf{P}_t = \begin{cases} \begin{pmatrix} 1 & 0 \\ 0.82 & 0.08 \end{pmatrix} & \text{if } d_t = 0 \\ \begin{pmatrix} 0.67 & 0.32 \\ 0 & 1 \end{pmatrix} & \text{if } d_t = 1 \end{cases}$$

Smoothed Probabilities

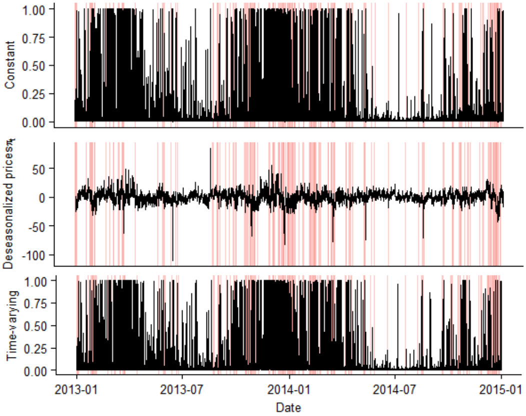

Figure 5: Probability of being in state $s = 1$ together with deseasonalized price and Wind Penetration Indicator (red shades)

Forecast Evaluation

	MAE	SD
Constant	5.97	(0.07)
Time-varying	5.13	(0.08)
Persistent	9.87	(0.14)
ARIMA	6.24	(0.09)

Table 2: Forecast evaluation based on Mean Absolute Error (MAE). Standard deviation in parenthesis.

Conclusion and Outlook

- Flexible Model
- Integrate effect of wind power production
- Capture Spikes
- Good forecasting performance

- Possible extensions
    - Continuous effect of wind
    - Heavy-tailed distribution for jump regime

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Merit Order

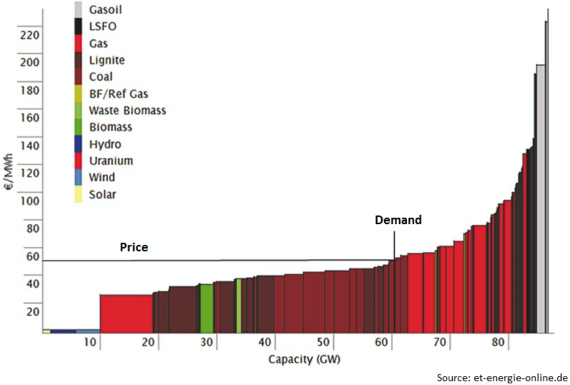

Figure 6: Merit Order Pricing

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