The impact of renewable energy production on tail events of electricity spot price indices

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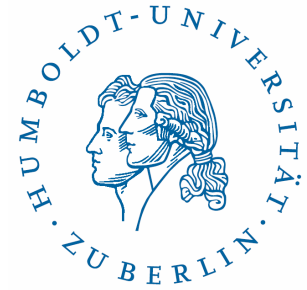


Residual load and Spot Price

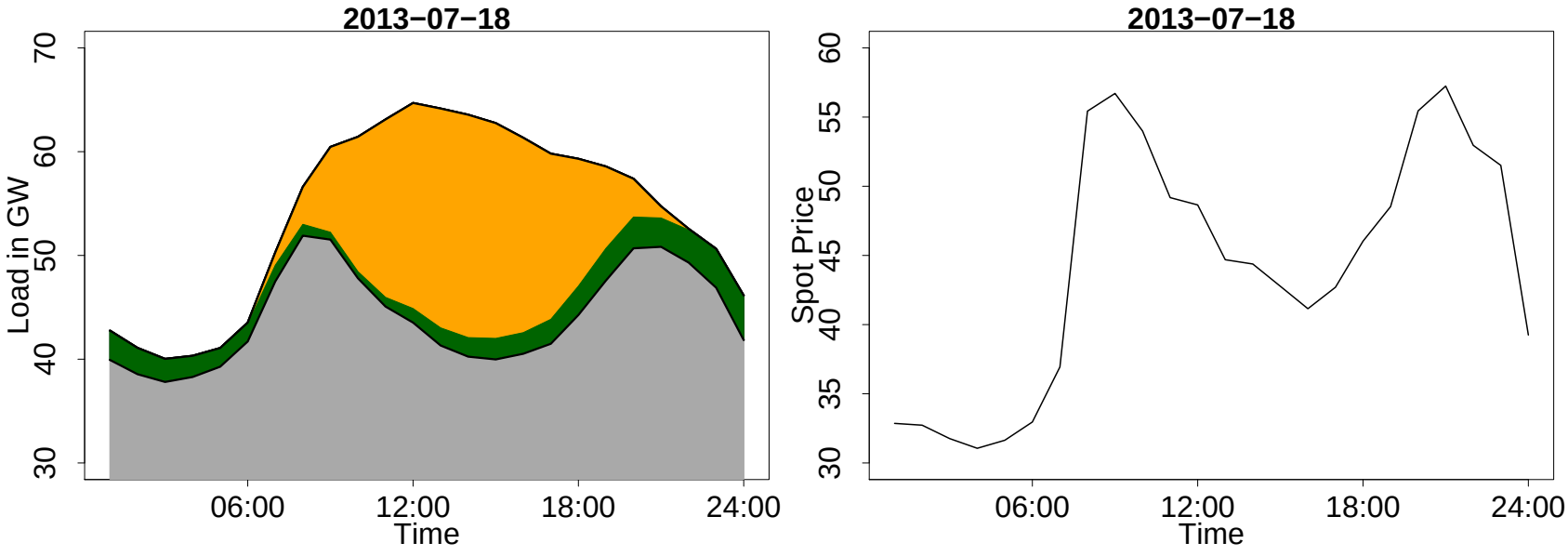
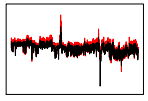


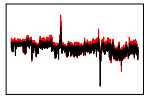
Figure 1: Left: Total consumption (black line), solar infeed (orange), wind infeed (green) and residual load (grey) in Germany, Right: EPEX Spot Price



German Electricity Market

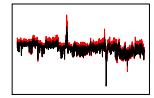
- Non-storable good
- Feed-in guarantee of renewable energy
- Inelastic demand
- Day-ahead single price auction
- Merit order ▸ Merit-Order

- Large price fluctuations
- Negative prices are possible



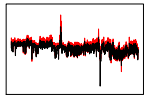
Residual Load and Spot Price

- Increasing installed capacity of renewable energy ▸ IC
- Level and volatility of electricity prices are determined by residual demand
  (residual demand = total demand − renewable infeed)
- Low demand + high renewable infeed lead to low or even negative prices and vice versa
- Not accounted for in most electricity price models



Spot Price Indices

- Spot price indices:
  - Phelix Day Base: average of 24 hourly spot prices
  - Phelix Day Peak: average of spot price during hours 9-20
- Traded at the German electricity exchange EEX
- Most common underlyings for electricity derivatives
- Reference price for European market



Residual Load and Phelix day base

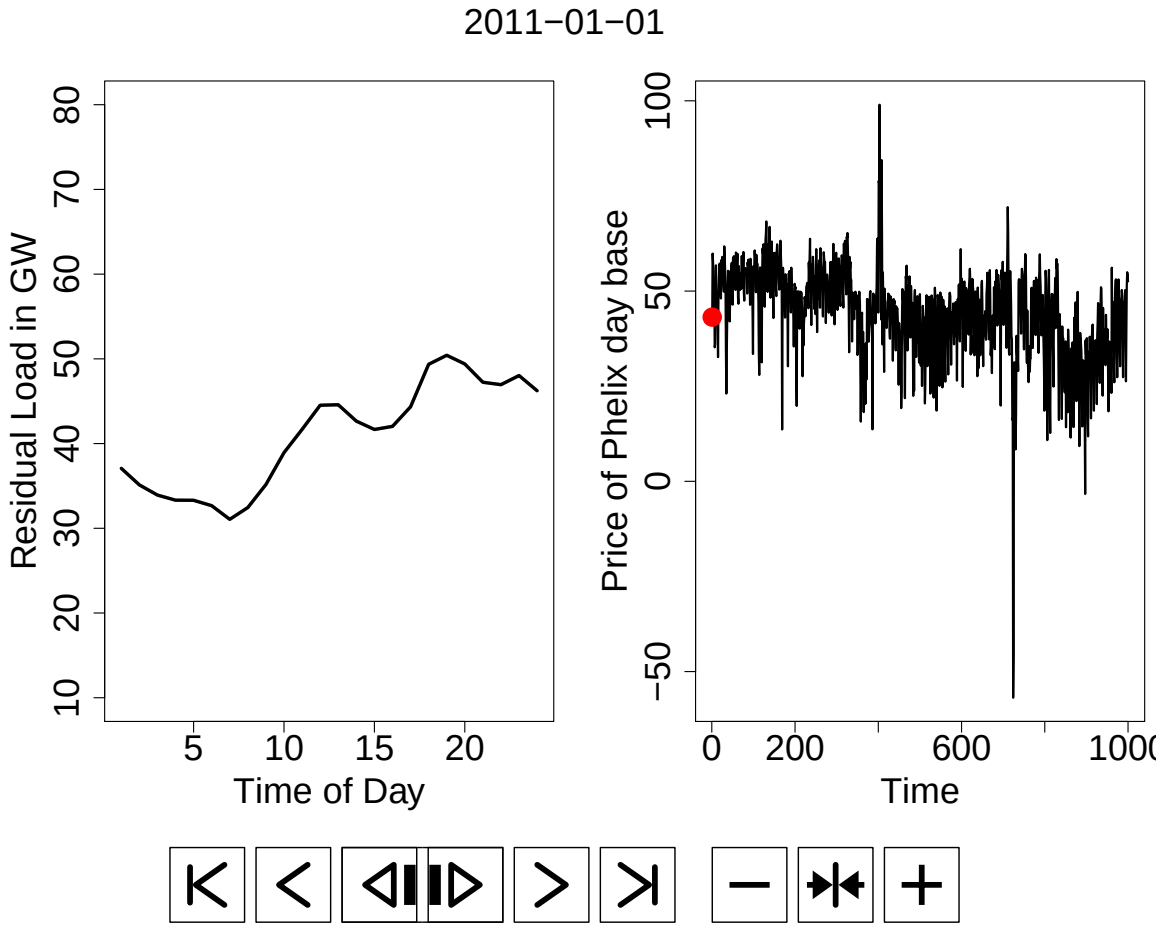
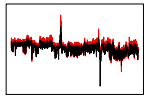
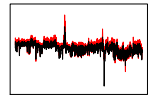


Figure 2: Residual load (left) and Phelix Day base (right)



Literature

- Hu (2009)
  - auction mechanism in liberalized electricity markets
  - load affects price level and dispersion
- Nicolosi and Fürsch (2008)
  - investigate impact of renewable energy infeed on the power market
  - residual load more volatile than total load
  - long-term market effects

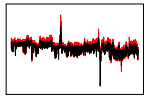


Objective

- Modeling residual load
  - FPCA
  - dynamics over time
  - dependence on meteorological variables
- Forecasting conditional distribution of spot prices indices
  - risk management
  - what is the effect of demand side management?

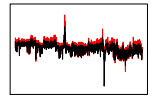
Challenges

- High dimensional regressors
- Unknown functional form
- Nonparametric functional regression



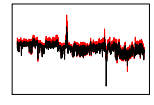
Outline

1. Motivation ✓
2. Data
3. Methodology
4. Results
5. Conclusion



Data

- Hourly consumption, wind and solar energy production for Germany from ENTSOE and TSOs
- Daily spot price indices:
  - Phelix Day Base
  - Phelix Day Peak
- Data from 20110101 to 20131231



Load data

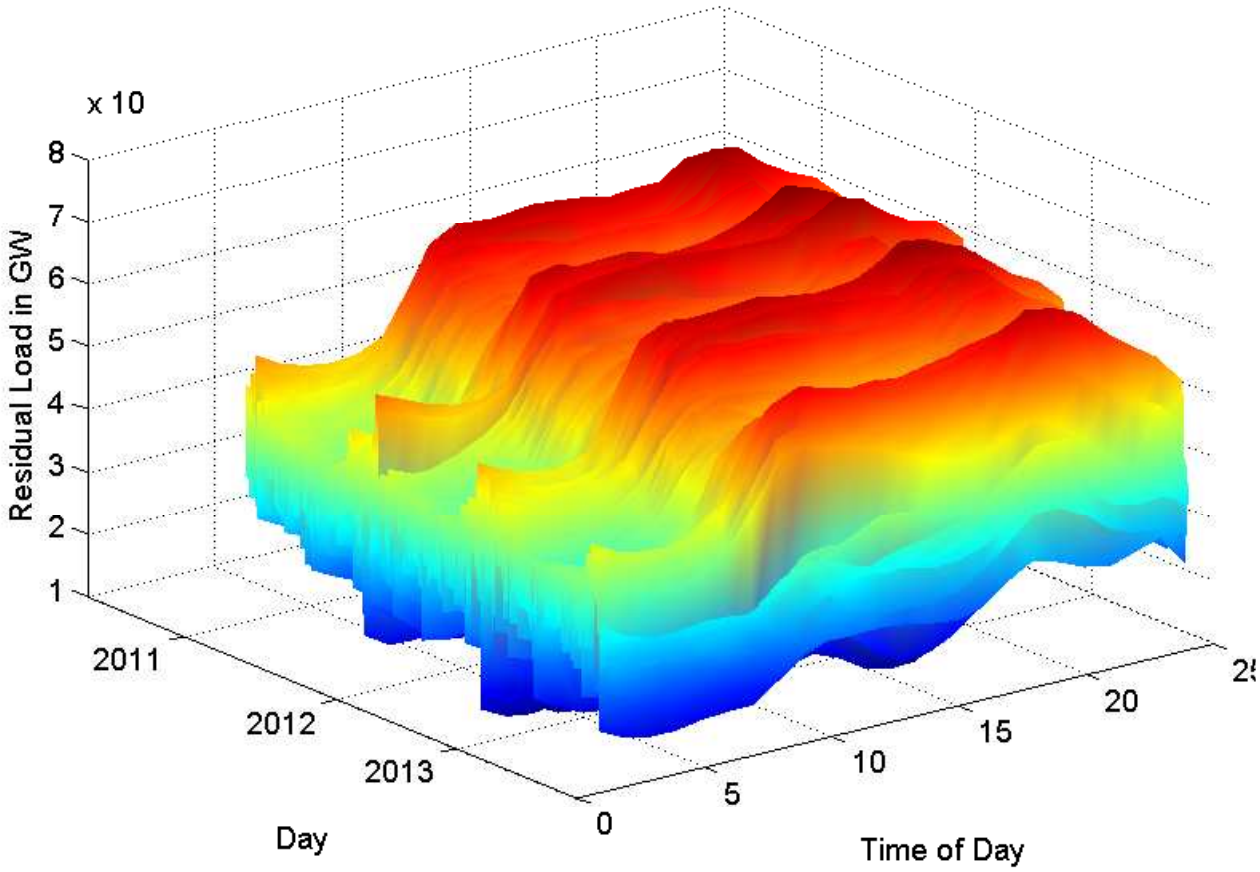


Figure 3: Residual load in GW

Price Data

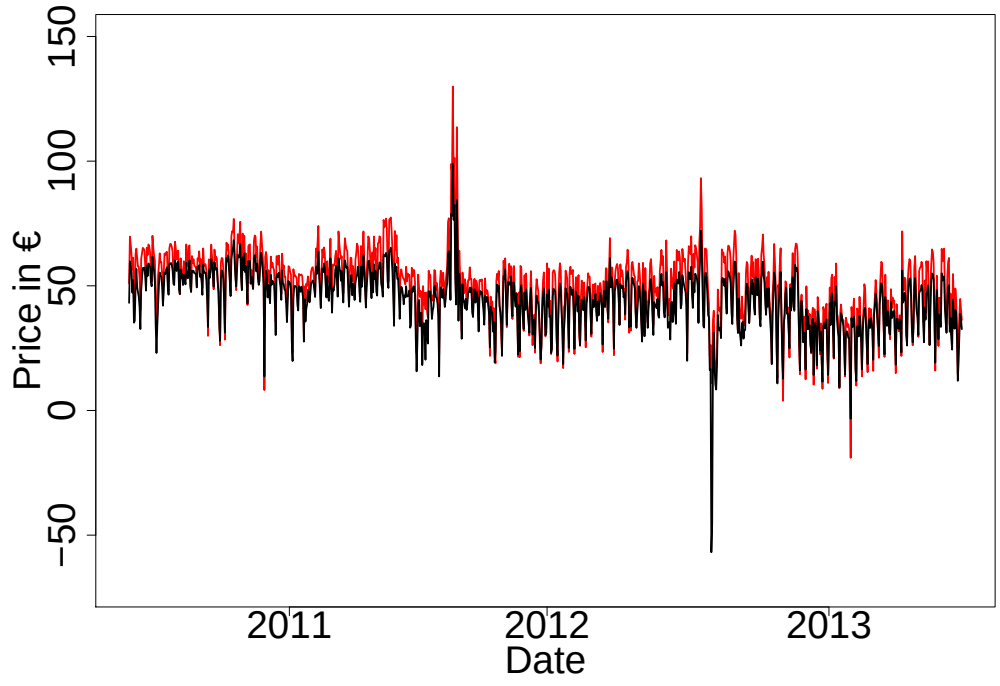


Figure 4: Residual Load and spot price indices: Phelix day base (black), Phelix Day Peak (red)

Statistical Model for Residual Load

- Residual load= deterministic seasonal component + stochastic component

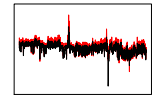
$$\tilde{X}_s = \Lambda_s + X_s, s = 1, \ldots, T \cdot K$$

- the seasonal component Λ_t is modeled as

$$\Lambda_{t,k} = a_t + b_t \cdot k + c_{1,t} \sin(\frac{2\pi k}{365}) + c_{2,t} \cos(\frac{2\pi k}{365}) + \sum_{i=1}^{7} d_{i,t} \cdot D_{i,k}$$

where

- $t = 1, \ldots, T$ denotes time within day, $k = 1, \ldots, K$ denotes day
- D_{it} is a set of dummies for weekdays and public holidays
- $a_t, b_t, c_{1,1}, c_{2,t}$ and $d_{i,t}$ are parameters to be estimated



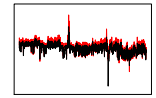
Statistical Model for Residual Load

- $X_k(t)$ is estimated by functional principal component analysis

$$X_k(t) \approx \mu(t) + \sum_{i=1}^{m} \alpha_{i,k}\phi_i(t), \quad \alpha_i = \langle X(t), \phi_i \rangle$$

- The estimated principal component score $\widehat{\alpha}$ are modeled using a vector autoregressive (VAR) model
- Possible to include external regressors, e.g. temperature, hours of sunshine, wind speed

$$\widehat{\alpha}_k = \sum_{i=1}^{p} \Phi_{k-i}\widehat{\alpha}_{k-i} + \beta x_k + \eta_k$$



Nonparametric functional mean and quantile regression

$$Y = r\{X(t)\} + \varepsilon$$

Conditional mean:

$$r(\chi) = \mathrm{E}\{Y|X(t) = x(t)\}$$

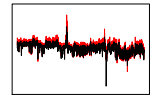
Conditional cdf:

$$\forall y \in \mathbb{R}, \quad F_Y^X\{X(t), y\} = P\{Y \leq y|X(t) = x(t)\},$$

Conditional quantile:

$$q_\tau(\chi) = \inf\{y \in \mathbb{R}, F_Y^X\{X(t), y\} \geq \tau\}, \quad \tau \in (0, 1)$$

Y is a real r.v.
$X(t)$ is a r.v. in functional space



Kernel regression estimator

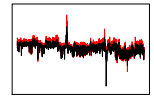
Estimator (Ferraty and Vieu, 2005):

$$\widehat{r}\{X(t)\} = \frac{\sum_{i=1}^{n} Y_i \, \mathrm{K}\left[h^{-1} d\{X(t), X(t)_i\}\right]}{\sum_{i=1}^{n} \mathrm{K}\left[h^{-1} d\{X(t), X_i(t)\}\right]} = \sum_{i=1}^{n} w_{i,h}\{X(t)\} Y_i$$

$$w_{i,h}\{X(t)\} = \frac{\mathrm{K}\left[h^{-1} d\{X(t), X_i(t)\}\right]}{\sum_{i=1}^{n} \mathrm{K}\left[h^{-1} d\{X(t), X_i(t)\}\right]}$$

where

- $\{X_i(t), Y_i\}_{i=1,\ldots,n}$ is a sample from $\{X(t), Y\}$
- K is a kernel
- h is a positive bandwidth
- $d(\cdot, \cdot)$ is a semi-metric ▸ semi-metric



Conditional quantiles

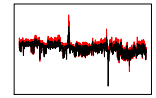
Conditional cdf of Y given $\boldsymbol{\chi}$:

$$\widehat{F}_Y^{\boldsymbol{\chi}}(\chi, y) = \frac{\sum_{i=1}^n Y_i \, \mathrm{K}\{h^{-1} d(\chi, \boldsymbol{\chi}_i)\} \, \mathrm{H}\{g^{-1}(y - Y_i)\}}{\sum_{i=1}^n \mathrm{K}\{h^{-1} d(\chi, \boldsymbol{\chi}_i)\}}$$

$$\widehat{q}_\tau(\chi) = \inf\{y \in \mathbb{R}, \widehat{F}_Y^{\boldsymbol{\chi}}(\chi, y) \geq \tau\},$$

where

- K is a kernel, $\mathrm{H}(u) = \int_{-\infty}^{u} \mathrm{K}_0(v) dv$ is a cdf
- h, g are positive bandwidth parameters
- $d(\cdot, \cdot)$ is a semi-metric



Residual Load

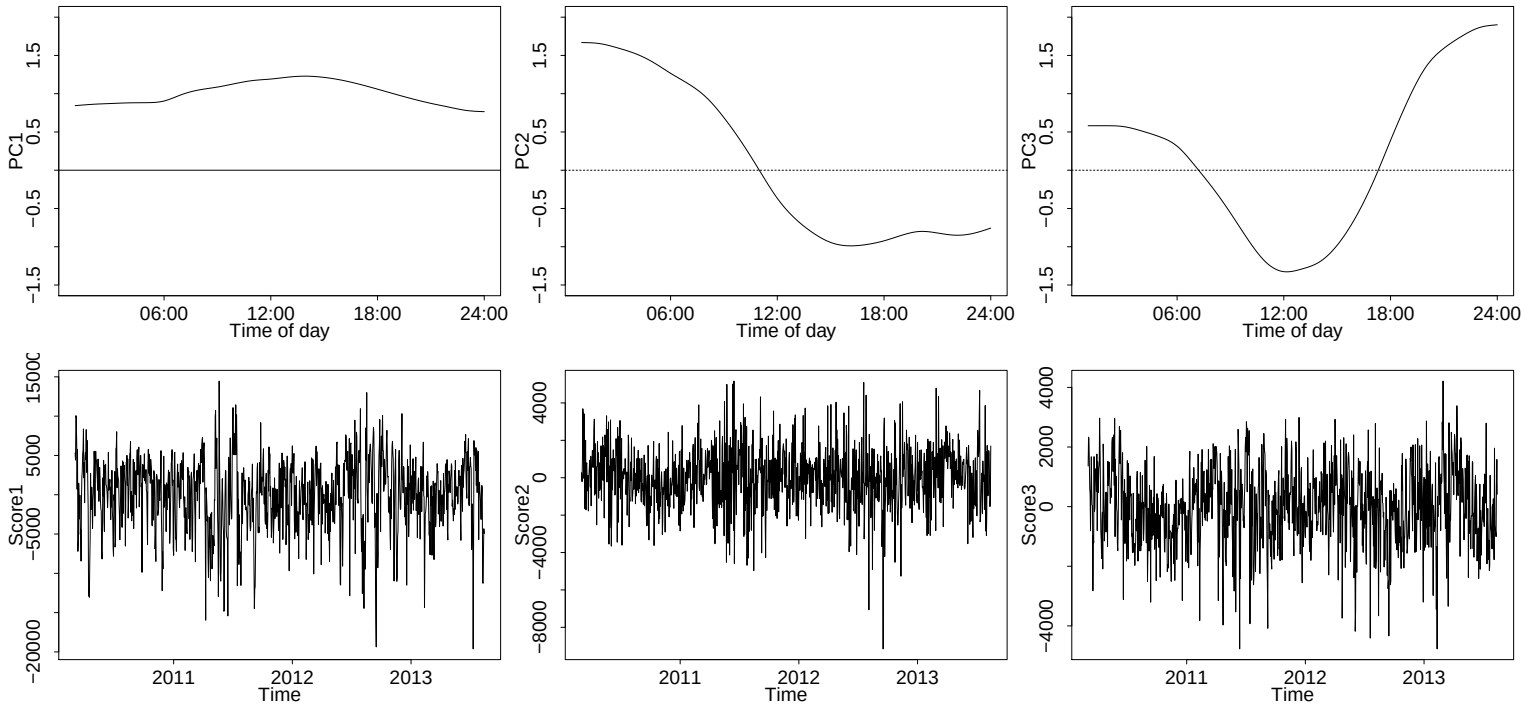
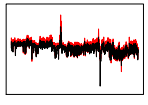


Figure 5: The first three principal components, explained variance 95% (upper panel) and the corresponding principal component scores (lower panel)



Estimation Results

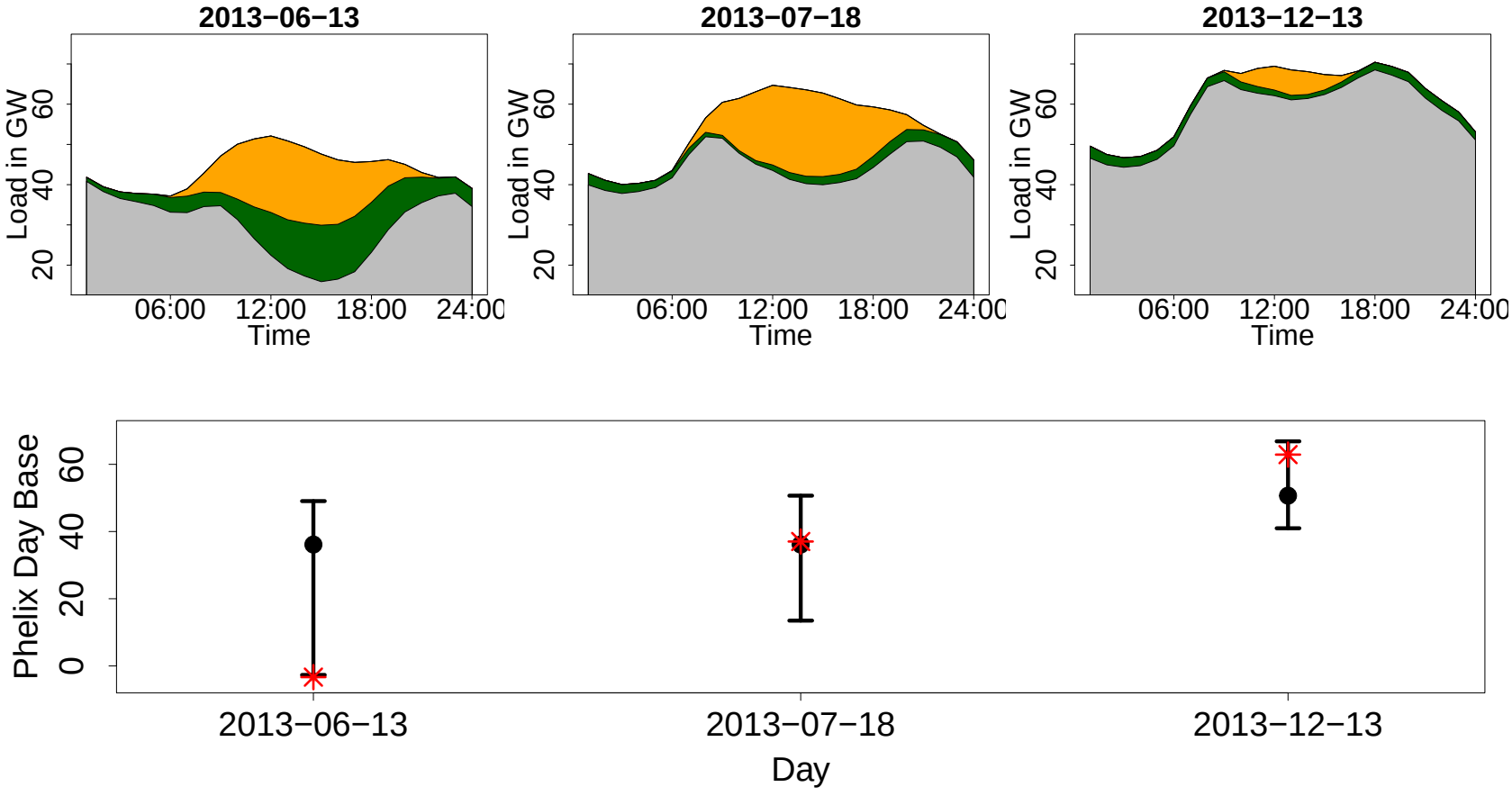
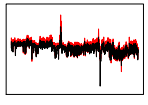


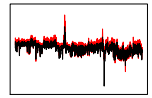
Figure 6: Residual load and interval forecasts of price index



Point Forecast Evaluation

	NPFMR	Benchmark
RMSE	8.70	11.87
MAPE	0.026	0.034

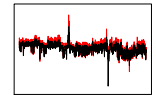
Table 1: RMSE and MAPE for nonparametric functional mean regression (NPFMR) and nonparametric mean regression using average daily load (benchmark) based on 365 out-of-sample forecasts



Interval Forecast Evaluation

	NPFQR	Benchmark
Average length	27.26	30.84
Unconditional Coverage	0.912	0.961
LR Test of Unconditional Coverage (p-value)	0.472	<0.01
LR Test of Conditional Coverage (p-value)	0.015	<0.01

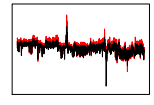
Table 2: Forecast interval evaluation for $\tau = 0.05, 0.95$ of nonparametric functional quantile regression (NPFQR) and nonparametric quantile regression using average daily load (benchmark)



Conclusion and Outlook

- FPCA for residual load
- Interval forecasts of spot price index using NPFDA
- Forecasts outperform naive benchmark model

- Time-varying quantile regression
- Variable selection



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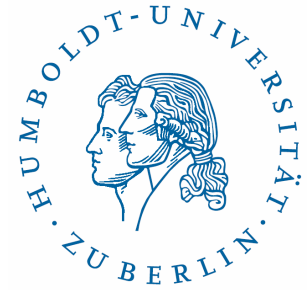

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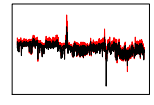

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The impact of an increasing share of RES-E on the Conventional Power Market - The Example of Germany
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Merit Order

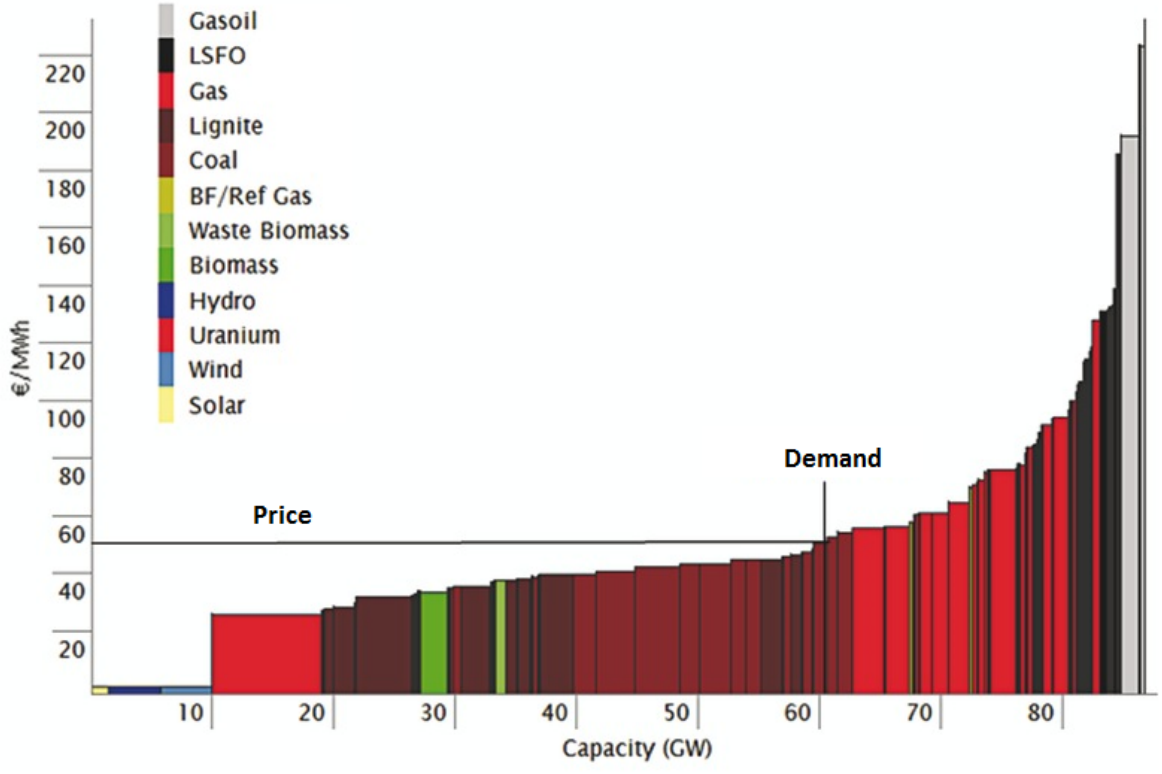
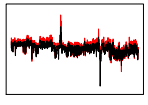


Figure 7: Merit Order Pricing

Return



Installed Capacity

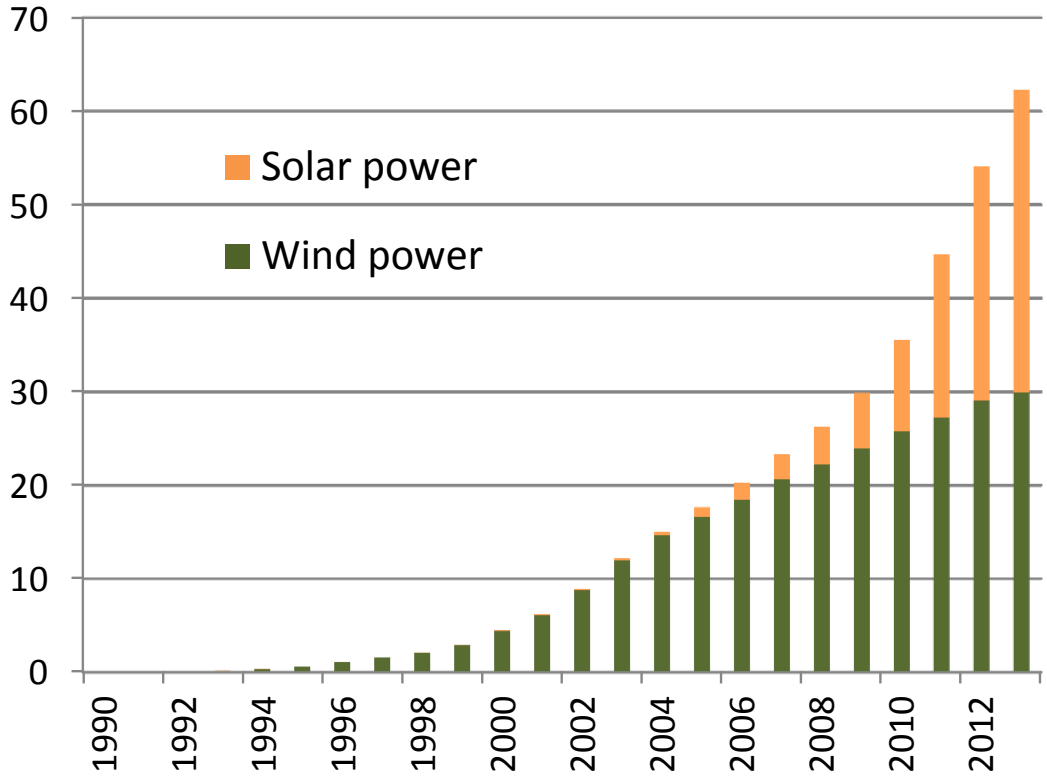


Figure 8: Installed Capacity of renewables in GW

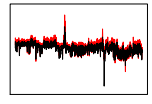
Return

Semi-metric based on PCA

Return

$$d_q^{PCA}(X_i, x) = \sqrt{\sum_{k=1}^{q} \left[\int \{X_i(t) - x(t)\} v_k(t) dt \right]^2}$$

$$d_q^{PCA}(x_i, x_{i'}) = \sqrt{\sum_{k=1}^{q} \left[\sum_{j=1}^{J} w_j \{x_i(t_j) - x_{i'}(t_j)\} [v_k]_j \right]^2},$$

where

- $x_i = \{x_i(t_1), \ldots, x_i(t_J)\}$ and $x_{i'}\{x_{i'}(t_1), \ldots, x_{i'}(t_J)\}$ are discretized curves
- $v_1, \ldots, v_q$ are the first q eigenvectors of the covariance matrix of the x_i
- w_j are weights