Institute for Operations Research
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The impact of renewable energies on EEX day-ahead electricity prices

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Promotion of renewable energies in Germany

- **Renewable Energy Act (EEG, 2000)**:
  - Producers of renewable energies (wind, PV etc.) receive a guaranteed compensation (technology dependent feed-in tariffs)
  - The additional costs of renewable energy sources are apportioned to energy suppliers, which pass it ultimately to end consumers through the EEG surcharge

- **First phase of the implementation (2000-2009)**: significant increase in electricity production from renewable energy sources
  - The high volume of PV installations made feed-in tariffs unbearable
  - The EEG surcharge increased due to the increasing production from renewable energy sources

- In a **second phase (2009-2011)**: the transmission grid is not capable to handle the growing supply of fluctuating renewable energies
  - Most wind capacities are installed in the north of Germany, while energy consumption is concentrated in the south
  - In regions with *high supply* of renewables, modern and efficient power plants are shut down to avoid a potential grid breakdown
  - In regions where *the grid is not fully developed*, more expensive (oil-fired) plants must run to stabilize the grid

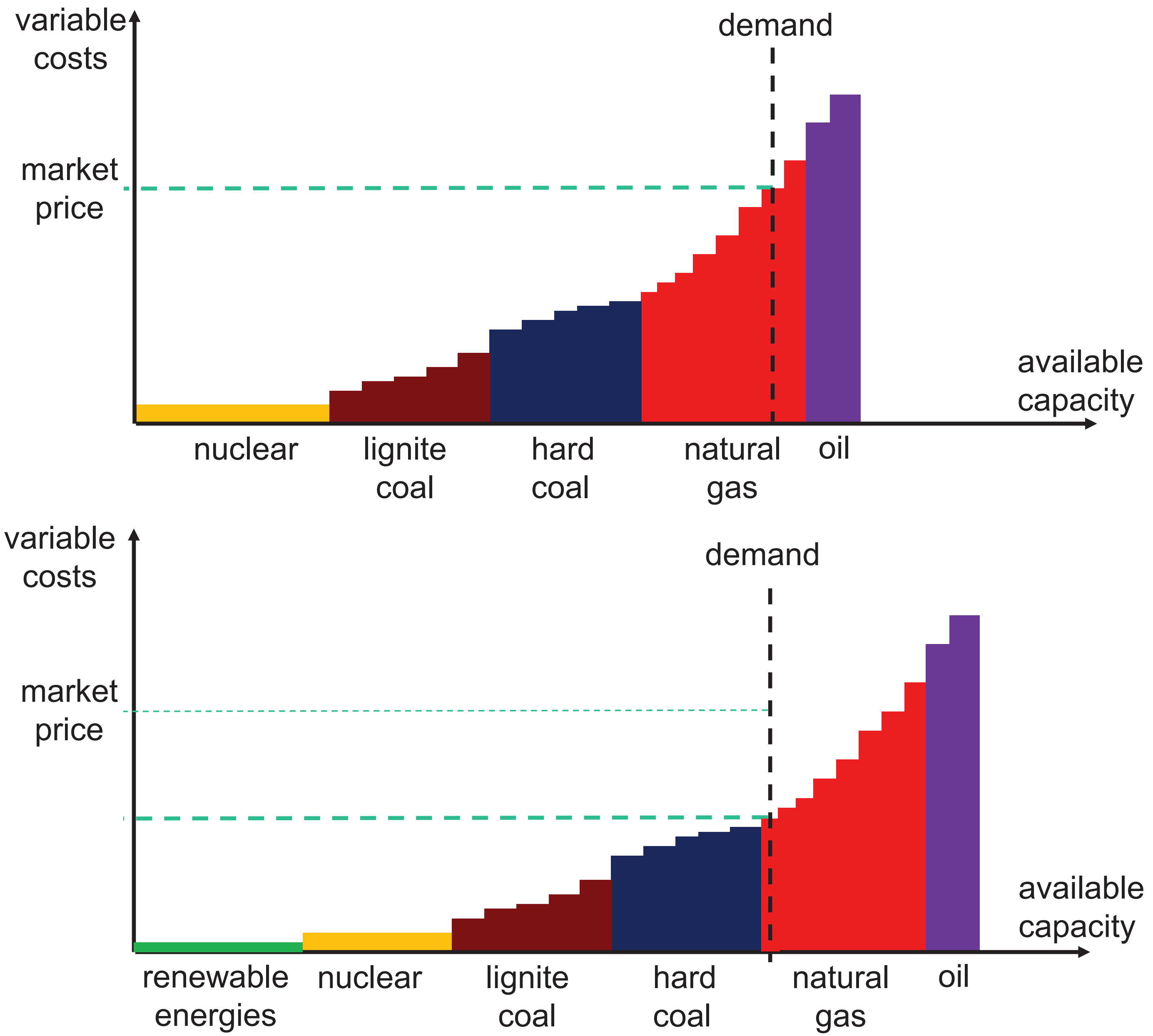
Renewables - shift in the merit order curve

- There was a significant increase in the use of renewable energies during the investigated period
- This caused large changes in the supply mix

	2009	**2010**	**2011**	**2012**	**2013**
Coal	42.6	41.5	42.8	44	45.2
Nuclear	22.6	22.2	17.6	15.8	15.4
Natural Gas	13.6	14.1	14	12.1	10.5
Oil	1.7	1.4	1.2	1.2	1
Renewable energies from which	**15.9**	**16.6**	**20.2**	**22.8**	**23.9**
Wind	6.5	6	8	8.1	8.4
Hydro power	3.2	3.3	2.9	3.5	3.2
Biomas	4.4	4.7	5.3	6.3	6.7
Photovoltaic	1.1	1.8	3.2	4.2	4.7
Waste-to-energy	0.7	0.7	0.8	0.8	0.8
Other	3.6	4.2	4.2	4.1	4

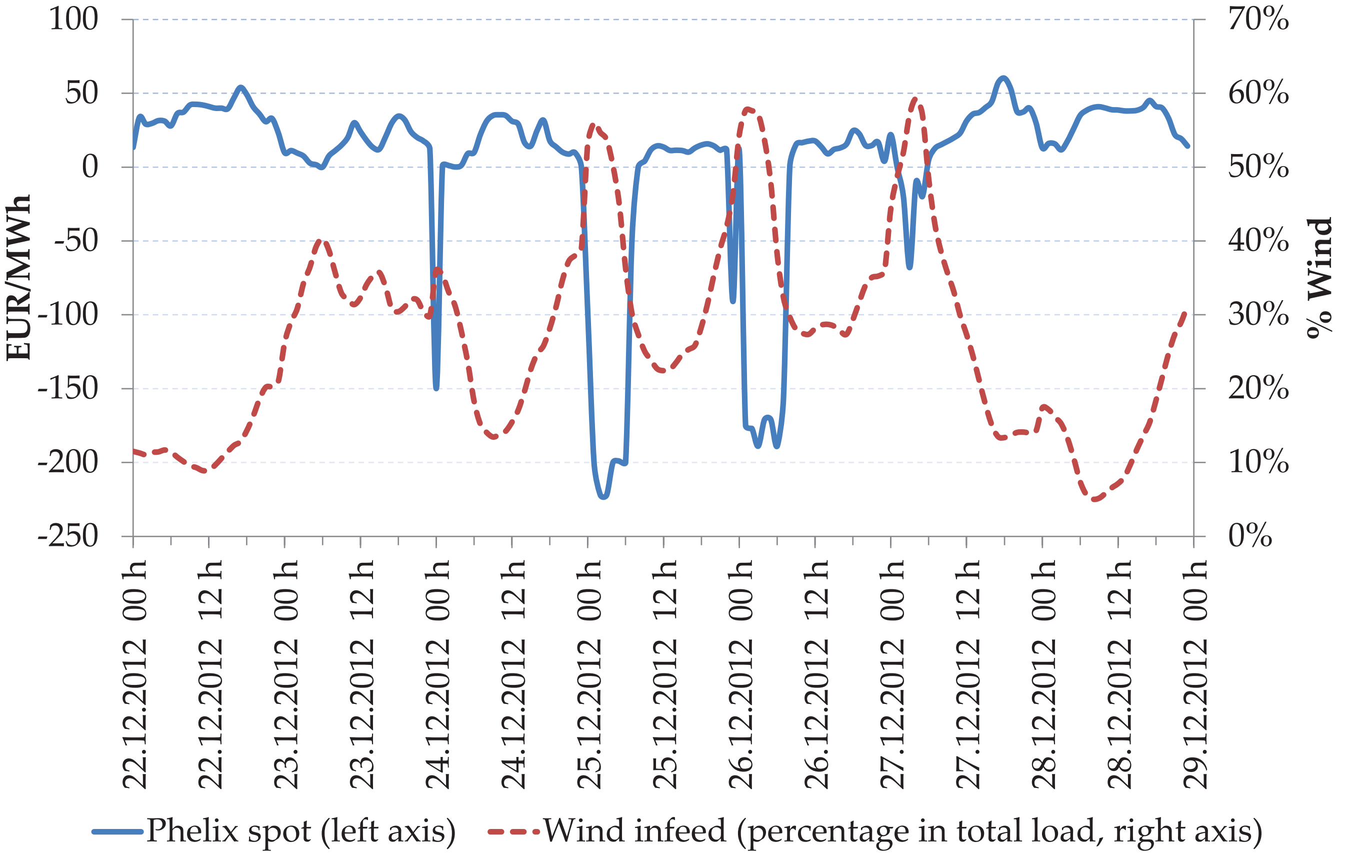
Table 1: Electricity production in Germany by source (%). Source: AG Energiebilanzen e.V. [2014]

Renewables - shift in the merit order curve



Renewables and extreme events

- In case of excess supply of electricity, prices can fall down to zero or even below:
  - Renewable energies are fed in with priority
  - A large conventional (nuclear or coal-fired) plant is less flexible and cannot be shut down or ramped up immediately, only at high costs; therefore operators are willing to accept a negative prices



Market fundamentals driving electricity prices

- **PHELIX prices (01/01/2010–28/02/2013)** for each hour ($i = 1, \ldots, T$) modeled separately by the following fundamentals:
  - **Demand:** demand forecast not available for all TSO zones!

$$Demand_{i,t} = \alpha_i + \varrho_i Demand_{i,t-1} + \beta_i' x_{i,t} + \varphi_i \varepsilon_{i,t-1} + \varepsilon_{i,t} \quad (1)$$

for hour i at day $t = 1, \ldots, T$; $\varepsilon_{i,t} = \sqrt{\sigma_{i,t}^2} u_{i,t}, \; u_{i,t} \sim N(0,1)$ with:

$$\sigma_{i,t}^2 = \omega_i + \phi_i \varepsilon_{i,t-1}^2 + \psi_i \sigma_{i,t-1}^2 \quad (2)$$

  - ▹ $x_{i,t}$ represents exogenous variables;
    - **Seasonal effects** modeled by dummy variables
    - **Climatic data:** sunshine duration, mean degree of cloud cover, maximum air temperature, mean relative humidity and cooling degree days (*Hamburg, Berlin, Dusseldorf, Munich*)
  - **Supply:**
    - ▹ Prices for **coal**, **gas**, **oil**, **CO2** emission allowances
    - ▹ Expected infeed from renewable energies (**wind**, **PV**)
    - ▹ Expected power plant availability (**PPA**)
  - **Learning effects:** lagged average spot price; lagged volatility

Dynamic fundamental model for electricity prices

- We assess the inter-temporal changes in the relation of hourly day-ahead electricity prices and market fundamentals in the context of a **time-varying regression model**
- Preliminary stability tests (following Brown et al. (1975), Karakatsani et al. (2010)) show strong evidence for time-varying parameters
- We formulate a **state space model** that allows for changing regression coefficients over time and estimate it with the **Kalman Filter** and **maximum likelihood**:

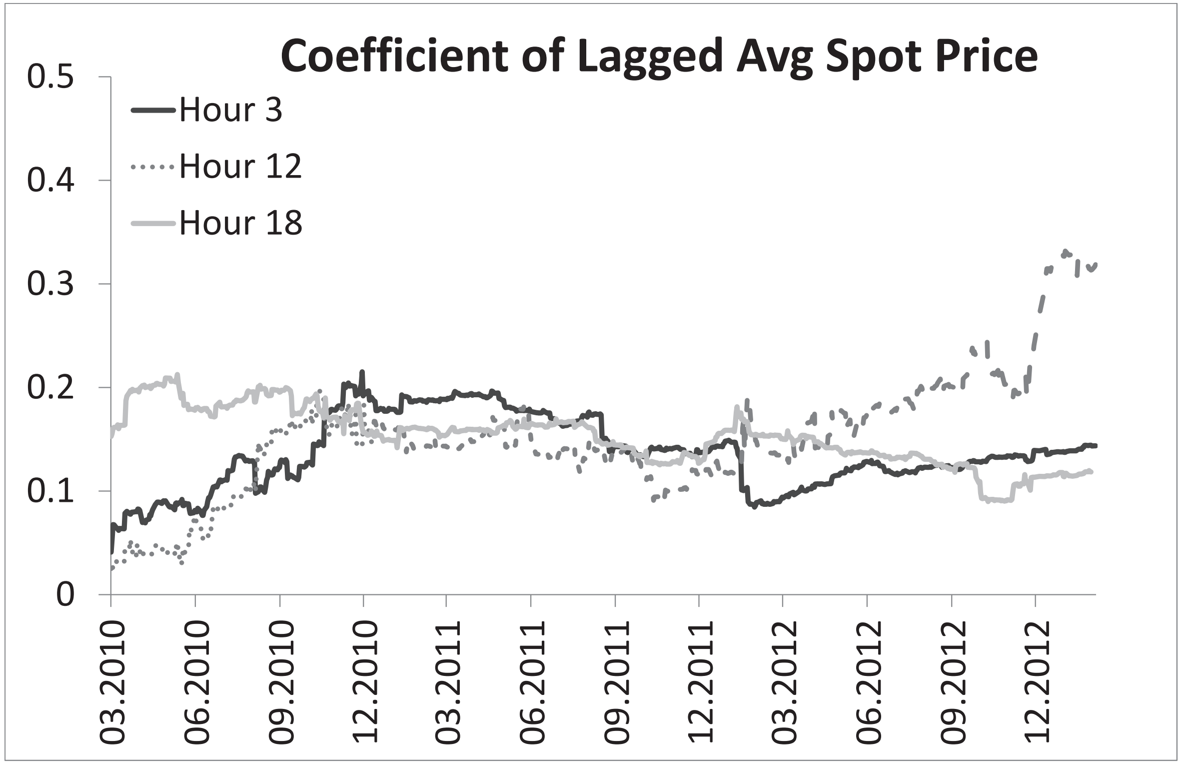
$$
\begin{aligned}
y_{i,t} &= z'_{i,t}\beta_{it} + v_{i,t} && \textit{Measurement Equation} \\
\beta_{i,t} &= c_i + d_i * \beta_{i,t-1} + w_{i,t} && \textit{Transition Equation}
\end{aligned}
$$

where $i \in \{1, ..., 24\}$ is the index for the hour and $k \in \{1, ..., 11\}$ variable index.

$$
\begin{aligned}
v_{i,t} &\sim \mathcal{N}(0, R_i) & E(v_{i,t}w_{i,t}) &= 0 \\
\beta_{i,t} &= (\beta_{i,1,t}, \beta_{i,2,t}, ..., \beta_{i,k,t})' & Q_i &= diag\{\sigma^2_{w_{i,1}}, \ldots, \sigma^2_{w_{i,k}}\} \\
w_{i,t} &= (w_{i,1,t}, w_{i,2,t}, ..., w_{i,k,t})' & d_i &= diag\{d_{i,1}, d_{i,2}, ..., d_{i,k}\} \\
w_{i,t} &\sim \mathcal{N}(0, Q_i) & c_i &= (c_{i,1}, c_{i,2}, ..., c_{i,k})'
\end{aligned}
$$

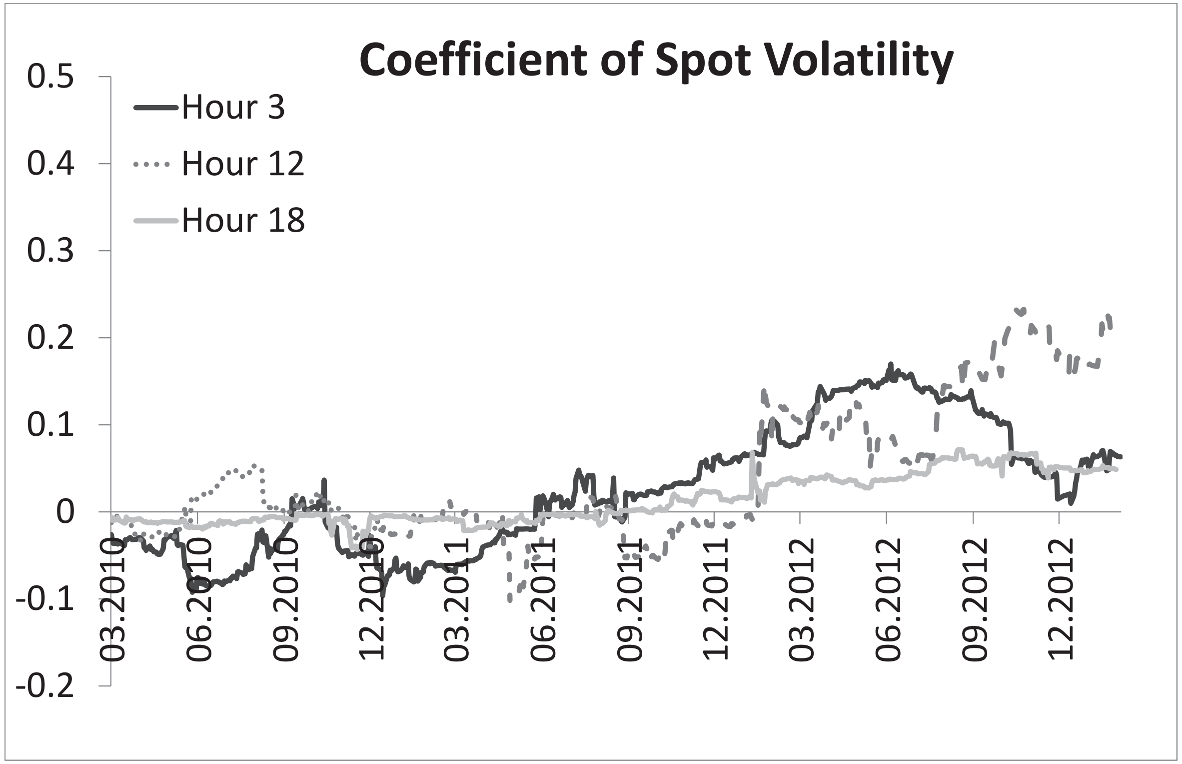
Results: Learning

- Consistent with discussion in literature (Bunn et al., 2014): one would expect a positive elasticity of spot prices to lagged prices (signal from last day)
  - Market agents tend to reinforce previously successful offers in the market which preserves price level
  - Signaling between agents keeps prices moving in the same direction



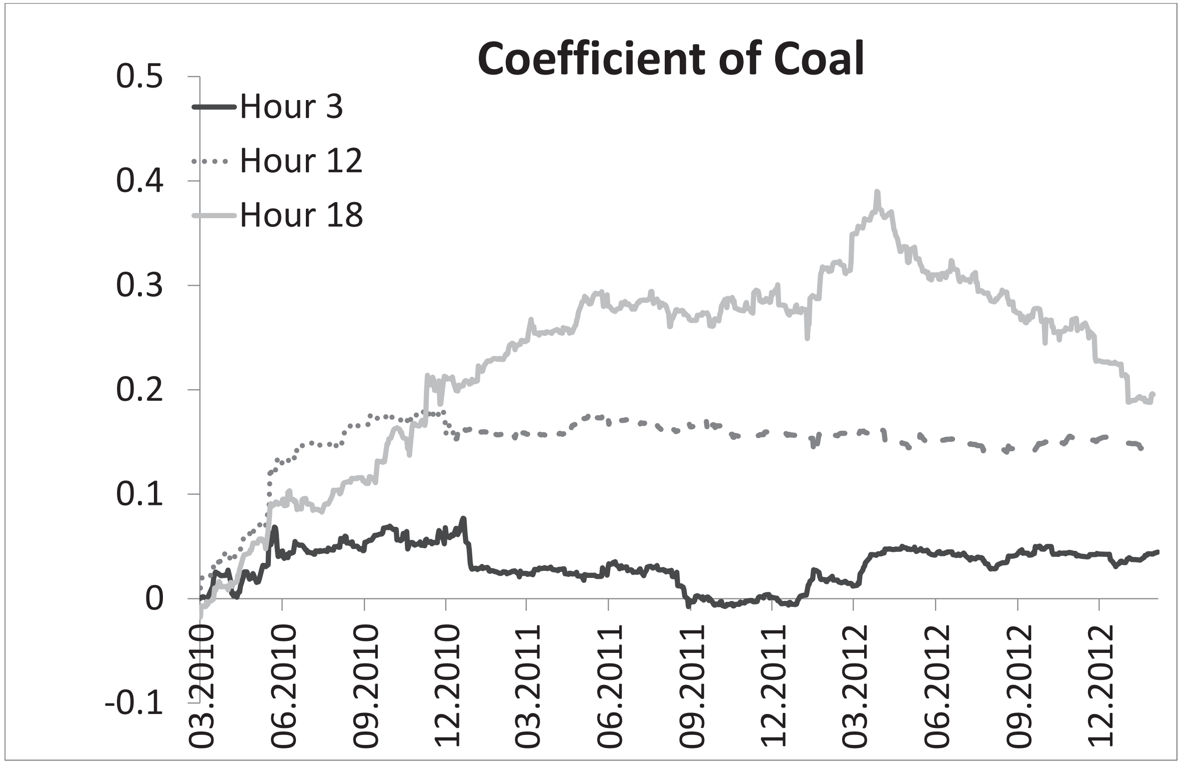
Results: Volatility

- Coefficient changed from negative to positive after 2011
  - Increase may be associated with **higher infeed of volatile renewable energies**
  - Impact of volatility on prices can be interpreted as **compensation for risk**
  - **Hedging** of price risk via spot market **became more expensive**



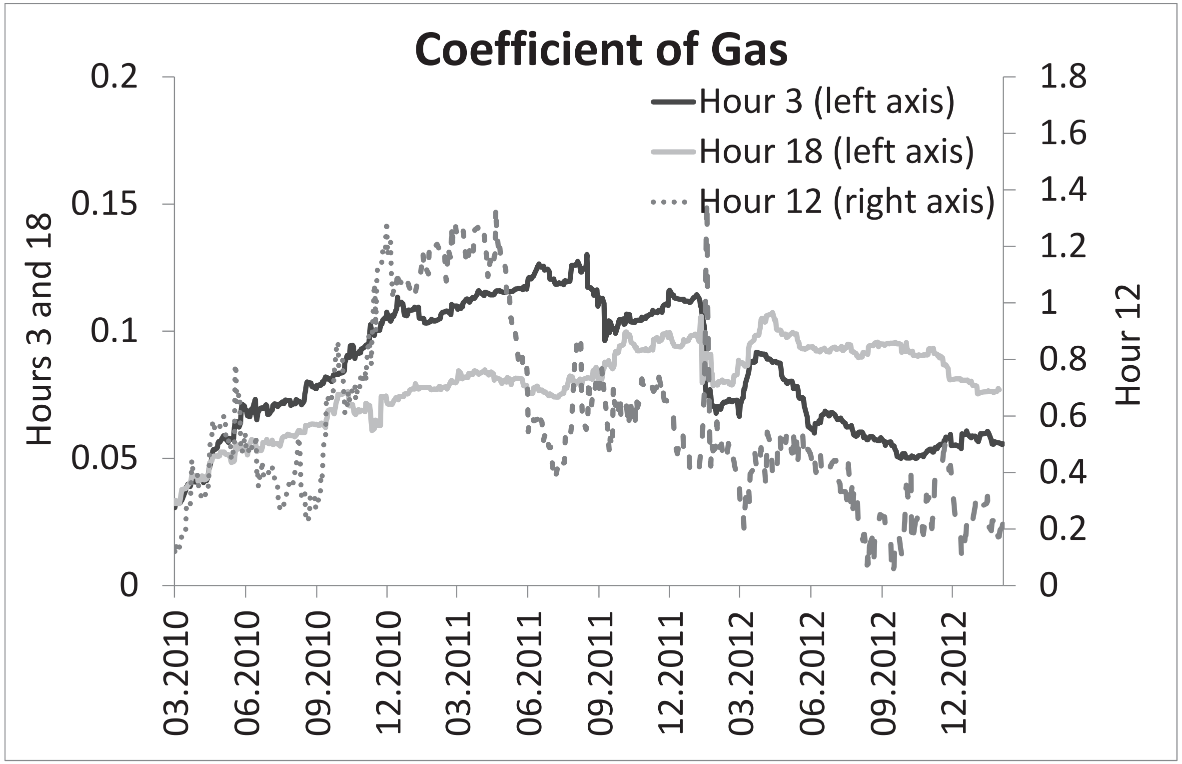
Results: Coal

- More distinct marginal effects for hours with high demand, in particular hour 18 (production mainly coal based)
- Coal is still most relevant fuel for electricity production in Germany, therefore we observe less price adaption w.r.t. coal than for gas



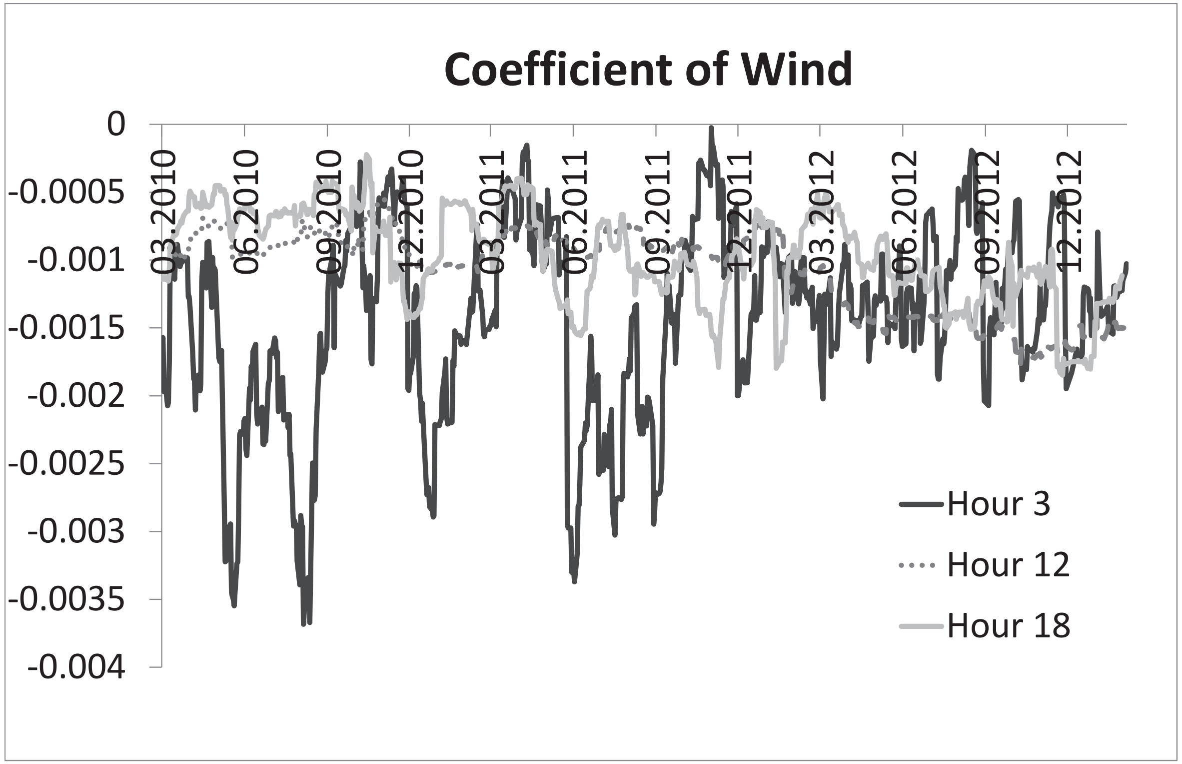
Results: Gas

- Gas and oil fired plants run in hours of high demand: we observe higher marginal effects for hour 12 (gas: see right axis)
- Continuous price adaption process, coefficients quite variable
- Since 2011 decrease in coefficients for gas particularly for hour 12 due to growth in PV infeed (highest around noon)



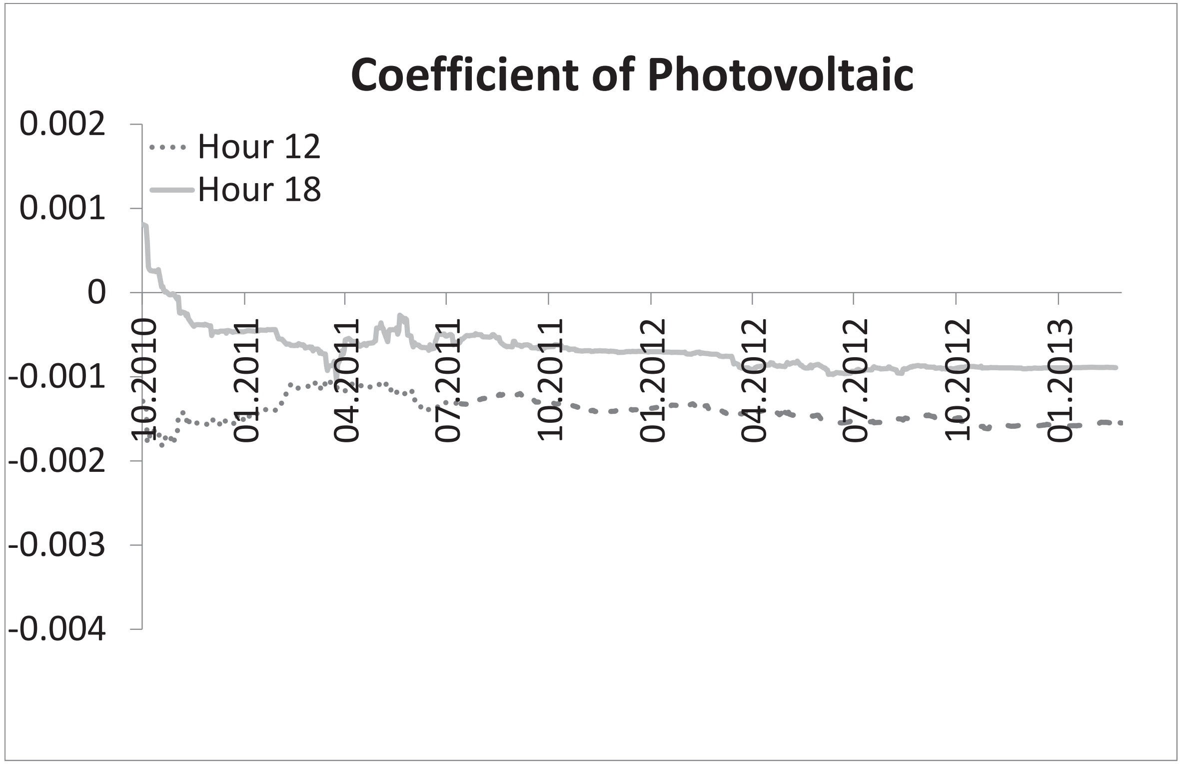
Results: Wind

- Negative coefficients imply that **wind infeed decreases prices**
- Variable price adaption process, particularly at night hours
- During the night, an excess of produced electricity meets a low demand: **negative prices** may occur which are caused to a large extent by wind infeed

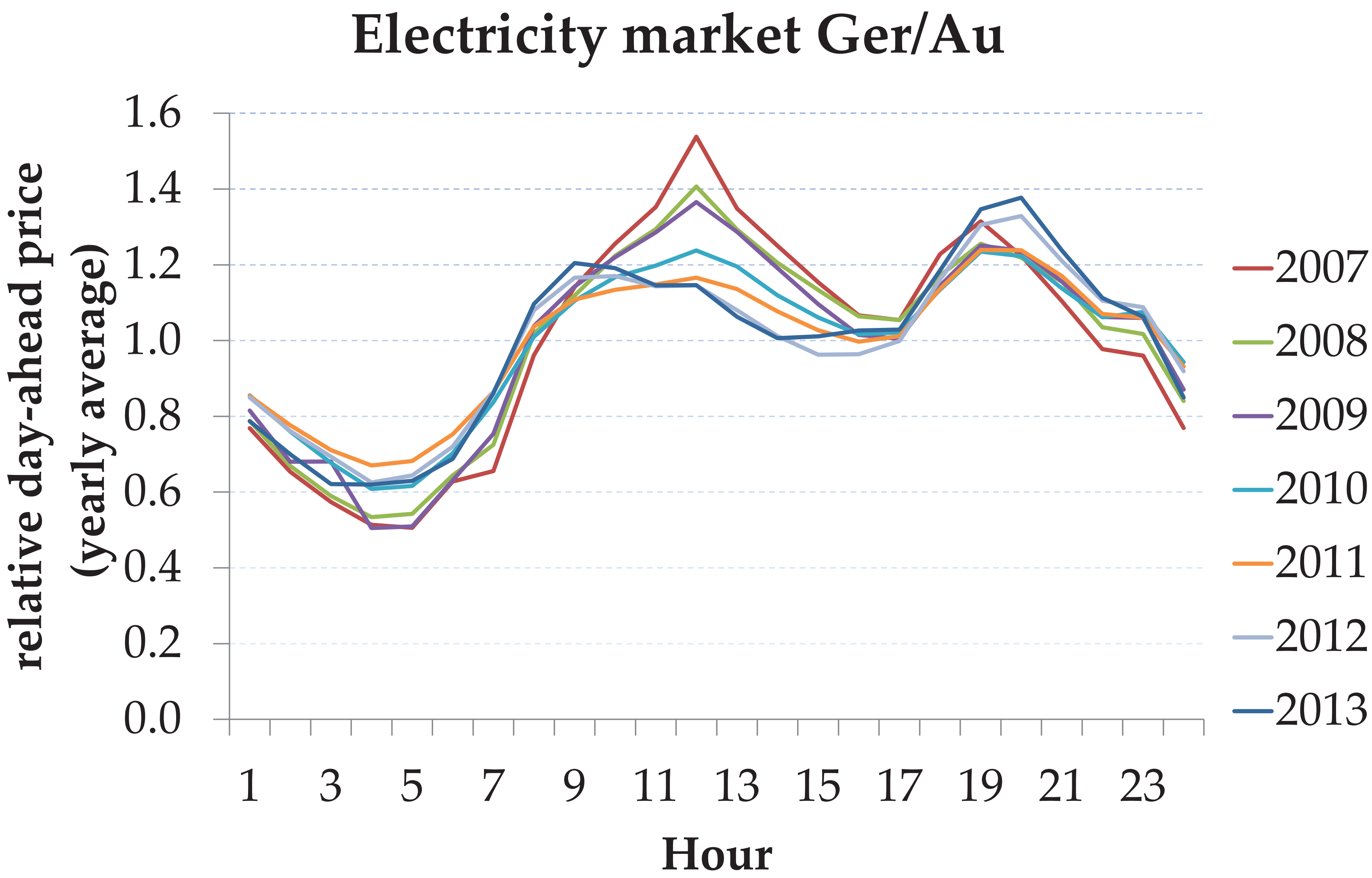


Results: PV

- Again, the negative sign implies that PV infeed decreases prices
- Little price adaption
- The impact on the price reduction is higher at noon

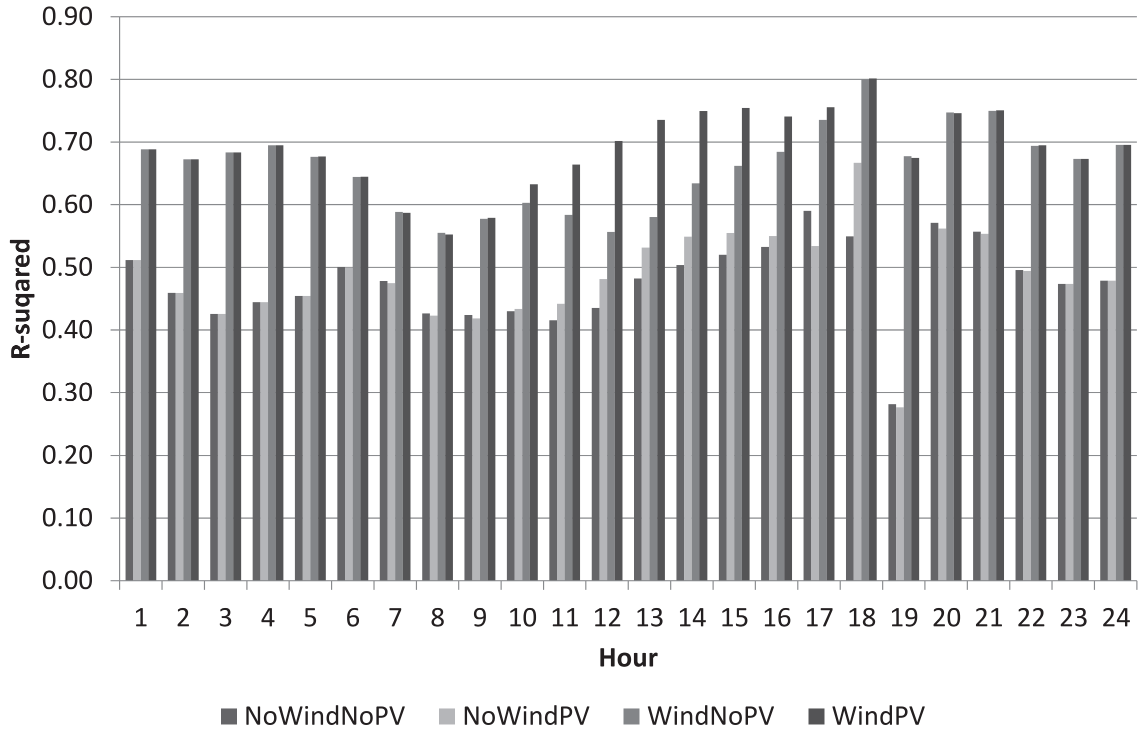


Dynamics relative day-ahead prices



Results: Statistics

- **Model residuals show no/very low autocorrelation:** The adaptive nature of the price structure is a possible source for the observed autoregressive structure in the volatility of electricity prices.
- The inclusion of renewable energies improves considerably the explanatory power of the model:



Conclusion

- There is a continuous **adaption process** of electricity prices to some market fundamentals: agents' learning, regulatory announcements, or stressed events in electricity markets
- Dependent on the time of the day, **fundamentals can have different marginal effects on the price formation at EEX**
- The adaptive nature of the price structure is a possible **source for the observed autoregressive structure in the volatility of electricity prices**: purely stochastic models can be a too simplistic assumption in this case!!
- Renewable energies **substitute the use in production** of traditional fuels situated at the right of the merit order curve

Outlook

- The increase in the infeed from renewable energies, wind and PV, led to a decrease in electricity day-ahead prices in Germany: **winners vs losers?**
  - **Traditional produces** suffer from the generally lower price level that decreases their margins
  - **Private consumers** must carry higher electricity prices, since ultimately they finance the EEG surcharge (financial burden is by far not compensated by the lower day-ahead market prices)
  - Only the **energy-intensive industry**, which is excluded from the EEG surcharge, benefits from the decrease in the day-ahead prices
- The current market design does not compensate the provision of reserve capacity adequately
- Additionally, the excess supply from renewables in Northern Germany must be efficiently distributed to regions with excess demand, which requires enhancements of the electricity grid
- Future incentive schemes for the promotion of renewable energies should take these aspects into account, since the matters of production, storage, and transportation cannot be treated separately

Extensions (joint work with Derek Bunn and Sjur Westgaard)

- Are market fundamentals impacting electricity prices in a different way across **price quantiles**? Apply **quantile regressions**, as done in Bunn et al. 2014, Westgaard et al. 2014:
- The general dynamic quantile model may be written as:

$$y_t = f_t(\beta, x_{t-1}) + u_t \tag{3}$$

The conditional α level quantile is:

$$q_\alpha(y_t|\beta, x_{t-1}) = f_t(\beta_\alpha, x_{t-1}) \tag{4}$$

where β_α is the solution to

$$\min_\beta \sum_t \rho_\alpha(y_t - f_t(\beta, x_{t-1})) \tag{5}$$

The function $\rho(\cdot)$ is a loss function, specified as $\rho_\alpha(u) = u(\alpha - I(u < 0))$.
- **Problem: semi-parametric approach, no assumption on the distribution of residuals is made!**

The Skewed-Laplace (SL) connection

- Yu & Moyeed (2001) and Tsionas (2003) illustrate the link between the solution to the quantile estimation problem and the likelihood for the SL distribution
- The SL location-scale family, denoted $SL(\mu, \tau, \alpha)$ has density function:

$$p_\alpha(u) = \frac{\alpha(1-\alpha)}{\tau} \exp\left[-\rho_\alpha(\frac{u-\mu}{\tau})\right] \tag{6}$$

  where μ is the mode and $\tau > 0$ is a scale parameter.
- If it is assumed in (3) that $u_t \sim SL(0, \tau, \alpha)$ and is iid, then the likelihood function becomes:

$$L_\alpha(\beta, \tau; y, X) \propto \tau^{-n} \exp\left\{-\tau^{-1} \sum_{t=1}^{n} (y_t - f_t(\beta)) \times [\alpha - I_{(-\infty,0)}(y_t - f_t(\beta))]\right\} \tag{7}$$

- Since (5) is contained in the exponent of the likelihood, **the maximum likelihood estimate for β is equivalent to the quantile estimator in (5).**

Estimation procedure